EMPIRICAL ESSAYS ON THE EFFICIENCY OF HETEROGENEOUS GOOD AUCTIONS

A Dissertation

by

THOMAS ALLEN MARTIN IV

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

August 2009

Major Subject: Economics

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Approved by:

Chair of Committee,	Steven L. Puller
Committee Members,	James Griffin
	Rajiv Sarin
	Steven N. Wiggins
Head of Department,	Larry Oliver

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ABSTRACT

Empirical Essays on the Efficiency of Heterogeneous Good Auctions. (August 2009)

Thomas Allen Martin IV, B.A., The University of Texas at Austin

Chair of Advisory Committee: Dr. Steven L. Puller

A recent pursuit of the auction design literature has been the development of an auction mechanism which performs well in a multi-good setting, when the goods are not substitutes. This work began in earnest with the Federal Communications Commission spectrum license auctions in the early nineties and continues to this day. In a setting in which goods are not substitutes, the value of one good depends non-negatively on the quantities of other goods that are won. This type of interdependent value structure has proven difficult to account for in auction design. However, the need for mechanisms that account for such a value structure hinges on the magnitude of the interdependence, whose computation is an empirical exercise. I identify a setting in which to perform this computation.

I develop an empirical methodology that allows me to recover bidders' value functions in a multi-good auction setting. This methodology allows me to assess the magnitude of any interdependence in the goods' value structure. Since the auction setting that I analyze is a variation of the standard uniform price auction, which has been adapted for a multi-good setting, I am able to measure the benefit of having a direct revelation mechanism. This counterfactual study is performed by maximizing the value of the auction using the recovered bidder value functions.

I find evidence that there is an interdependent value structure in the setting. The counterfactual auction finds that the standard uniform price auction, adapted to a multi-good setting, performs poorly in the presence of such a value structure. The setting for this analysis is an auction for financial transmission rights held in Texas in 2002. The auction involved twenty two firms and collected almost $70 million in revenue. This research is the first to empirically assess efficiency in this type of auction setting.

To Thomas Allen Martin II

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Without my wife's love, encouragement and support, this work would not have been attempted, or finished. Thomas, Dylan and Patrick, I thank you for the inspiration and hugs before I left for, "daddy's office."

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INTRODUCTION

Auctions are employed when an economic actor seeks to sell a set of items of uncertain value. The uncertainty inherent in this setting is the reason why a seller prefers an auction in lieu of an alternative mechanism. For example, the seller could use the price mechanism, in the form of a posted price, to sell the set of items. This method presents the seller with the dilemma of choosing the posted price such that a specified goal is achieved. If the seller wishes to maximize the price at which the set will sell, then she must form expectations of buyers' valuations for the set and choose a price close to the highest valuation. In a world which buyers possess private information on the value of a set of goods, auctions may serve as a better means of selling than posted prices.

There are cases, however, when available auction mechanisms, while out-performing other mechanisms, nonetheless fail to achieve the goal of the seller. It is in these cases when an empirical assessment can inform auction theory as to the performance of the mechanism. The research carried out in this dissertation seeks to inform auction theory of the degree that a particular auction mechanism in a particular setting achieves its stated goal of selling a set of items to the economic actors who value them most highly. This research uses field data to quantify the inefficiency of a specific mechanism used in a multi-unit, multi-good auction. This research contributes to the empirical auction literature, which seeks to inform auction designers and policy makers on the effectiveness of certain auction formats that are being utilized ever more.

Governments, firms and other institutions are increasingly utilizing auctions to

This dissertation follows the style of the Journal of Economic Theory.

allocate goods, services and property rights to interested parties. These items include electromagnetic spectrum rights, forest harvesting rights, off-shore oil rights, public goods projects, electricity transmission rights and many others. In many cases these institutions wish to auction a set of items which includes many, heterogeneous components. Auction theory has largely been focused on developing mechanisms that allocate a single item to the bidder with the highest valuation. However, the last fifteen years has seen a flourishing literature develop to study auction mechanisms for a set of items, where the set consists of either many identical units of the same item, one unit of many different items, or many units of many different items. There are two, not necessarily independent, goals of this literature. The first is to develop mechanisms that maximize the efficiency of the resulting allocation of goods. The second is to develop mechanisms that maximize the revenue of the seller as a result of the auction.

Auction design has focused on both the goal of efficiency and revenue maximization. Often governments and non-profit institutions seek to maximize the efficiency of an auction on account of legal or regulatory strictures. Notwithstanding, these entities also put a lower bound on auction revenue. For example, an auction mechanism that allocates a set of goods most efficiently, but results in the winning set of bidders acquiring the goods for a price of zero would likely not be put into use. Hence, in certain cases auction designers must put acceptable weights on efficiency and revenue goals.

In this research, I focus exclusively on efficiency. The reasons for this are topical as well as institutional. The topical reason is that the science of economics is predominantly focused with maximizing welfare. When the efficiency of an auction is maximized, societal welfare is maximized. This is the measurement by which all economic outcomes are judged and is a powerful statement. The next reason is institutional. The particular auction that I study was required by a regulatory body to allocate the set of items efficiently. I proceed to empirically analyze the efficiency of an auction for financial transmission rights in the Texas electricity market. The auction I study took place in 2002.

Economic theory has been concerned with the question of efficiency since at least the 1960's, and a burgeoning literature has developed.[1] If efficiency is the goal and one believes we live in a world with consequential transaction costs, then the auction format which is developed and implemented for a particular set of goods is of great importance. For an inefficient auction allocation is likely to cause substantial reductions in social welfare. In cases when there are heterogeneous goods for sale, the auctioneer's problem can be much more difficult than the case of homogeneous goods. With heterogeneous goods, the auctioneer must ascertain whether the goods are complementary to one another in generating value to bidders. If the goods do not exhibit complementarities, then the auctioneer can employ any of several mechanisms which yield strong efficiency and/or revenue properties. If complementarities do exist, then standard efficiency results may not hold and the auctioneer should consider alternate mechanisms.

How important are complementarities in multi-good auctions? When complementary goods are auctioned simultaneously, whether in an ascending-bid or sealed-bid format, to what degree do bidders change their behavior to incorporate these complementarities? The FCC spectrum auctions provide a relevant exposition of the salient aspects involved in multi-good auctions with complementarities.[2] Previously,

[1] See Friedman [14].

[2] See Milgrom [27], McAfee and McMillan [25], Cramton [9] and Cramton [10] for an overview of the FCC spectrum auctions, and Hazlett [20] for a discussion of the reasons for the auctions.

the auction literature primarily focused on auctions involving one type of good. The FCC spectrum auctions made the study of multi-good auctions timely, since spectrum worth tens of billions of dollars were now allocated to firms using auctions. The most important aspect of multi-good auctions which the auction designer must take into account are the types of goods being auctioned. When the bidder valuation's of the goods being auctioned are additive, then the auction designer can ignore any cross good effects. Suppose we would like to auction one unit of two different goods. If the bidders' valuations of the goods are additive, then the auctioneer could run either sequential second price auctions or simultaneous second price auctions. In this case, these mechanisms are allocatively equivalent. If this were the case in the FCC spectrum auctions, then the design of the auctions would have been a less onerous task. However, it is widely believed that there are complementarities among geographic blocks of spectrum. These complementarities arise from the fact that mobile phone users value roaming across their home areas and traveling to and from major metropolitan areas. This leads to the spectrum for New York City and Los Angeles together being valued more highly than the sum of the individual values of those cities. The auction designers wanted to design the spectrum auction so that bidders could express these types of valuations. Ideally the designers would like to have possessed a direct revelation mechanism in which bidders could fully express their preferences with package or combinatorial bidding. Such a mechanism does not yet exist. The designers constructed a mechanism which allowed bidders to assemble packages of complementary goods, without the added burden of allowing package bidding. The auction mechanism used for the first FCC spectrum auction was the Simultaneous Ascending Auction and is described in Milgrom [26]. A great deal of research was done after the first auction FCC auction in 1993 to develop and experimentally test an auction mechanism which allows for bidders to bid on complementary packages of goods. After almost 15 years of theoretical and laboratory research, the FCC implemented its first successful combinatorial auction when it auctioned parts of the 700MHz spectrum in early 2008. The FCC used the auction mechanism discussed in Goeree and Holt [15] and Rothkopf et al. [30]. The auction collected revenues of almost $20 billion.[3]

Existing theory provides efficient mechanisms in multi-good settings, but only settings in which goods do not have complementarities.[4] When no complementarities exist between goods, *i.e.* when bidders have additive valuation functions, there exists a direct revelation mechanism for multiple good auctions in the Vickrey-Clarke-Groves (VCG) mechanism,[8, 16, 31]. In a VCG auction each bidder pays the opportunity cost of her participation in the auction. Since each bidder's expected payment is not a function of her bid, in equilibrium the dominant strategy for every bidder is to submit their valuations for all packages of goods. There are several practical implications involved with running a multiple good VCG auction. First, the bidders must specify a value for every possible package of goods for sale. With n goods, there are $2^n - 1$ possible packages. Even if the set of packages is narrowed down by some relevance criterion, the number of relevant packages to evaluate will remain all but infeasible even assuming a trivial cost of valuing packages for anything but very small numbers of goods. In addition to posing a problem for the bidders, applying the VCG mechanism requires the auctioneer to take on an extremely difficult computational problem. The auctioneer must find the set of non-overlapping bids which maximizes seller revenue. This is referred to as the computational complexity problem.[5]

[3]For more information on the results of this auction see: http://wireless.fcc.gov/auctions/

[4]The primary focus of the FCC auctions was e fficiency, since Congress mandated to the FCC that the resulting allocation of licenses be as efficient as possible.

[5]See Vohra and de Vries [32], Goeree and Holt [15] and Rothkopf et al. [30]

When we consider the probable complementarities between spectrum licenses, the VCG mechanism breaks down. Ausubel and Milgrom [4] discuss extensively the theoretical reasons for this breakdown. In short, economists did not have a mechanism to offer which would feasibly, much less efficiently, allow the FCC to auction geographically diverse spectrum licenses using package bidding at the time of the first round of FCC auctions. Economists developed the Simultaneous Ascending Auction format for this purpose.

The Simultaneous Ascending Auction used in the FCC spectrum auctions was shown by Milgrom [26] to be equivalent to a Walrasian tatonnement process that reaches a competitive equilibrium. One of the assumptions needed for this equivalence is that the goods being auctioned are *mutual substitutes*. This assumption is likely to fail in the FCC auctions, since blocks of spectrum are likely to exhibit complementarities.

The pertinent question is *how likely is it that blocks of spectrum are complementary?* If the answer is not likely, or that the complementarities are small, then the Simultaneous Ascending Auction suits the spectrum auctions well. However, if the answer is that the complementarities between blocks of spectrum are certainly there and substantial, then having an auction mechanism which achieves efficiency in the presence of complementarities is of no small consequence.

The size of complementarities is ultimately an empirical question. There are several tacks one could take to show the existence of complementarities in this case. The researcher could build a detailed model of firm behavior in the wireless market for which spectrum is a *sine qua non* input. To perform this analysis the researcher would need detailed information on the wireless firms' cost structure and market demand. In addition the researcher would need to specify a paradigm for oligopolistic competition in this market. Each of these tasks are far from trivial on several fronts, provided that the data for such an exercise exists and is available. For the moment, assume this exercise is feasible. With a model of firm behavior in hand, the researcher could derive a spectrum value function for each firm in the wireless industry. The value function would not only give us the form of any complementarities but would give us their magnitude as well. Since this direct approach is likely to be unsatisfactory and infeasible in this case, economists have taken an alternate path to quantify complementarities.

A more feasible tack would be to compile data which are thought to contribute to the complementarities present in blocks of spectrum and use them to explain bids which were submitted in the auctions. This is exactly the approach taken in Ausubel et al. [2] and Moreton and Spiller [28]. Ausubel et al. [2] regress the log of winning bids on control variables and measures of the marginal bidder's complementarities, which were based on the population covered by licenses won by the marginal bidder. They find a significant positive effect, thus producing evidence for the existence of complementarities. In Moreton and Spiller [28], they perform a reduced-form regression of the winning bid for each block of spectrum on a set of control regressors and a set which are thought to encapsulate the complementarities. The authors break up the regressors, which are thought to be determinants of the size of complementarities, into two types: local complementarities and global complementarities. Local complementarities arise between adjacent blocks of spectrum. Global complementarities arise across all regions of spectrum. For local complementarities, they used local population in adjacent licenses ultimately won by the bidder and the runner-up bidder. For global synergies, they used the population of all licenses ultimately won by the bidder and the runner-up bidder. They find "considerable evidence" for local synergies and "some" evidence for global synergies.

Bajari and Fox [5] look for complementarities in the C block spectrum auctions which took place in 1995 and 1996. They use a novel estimator to uncover complementarities. They estimate a structural model of bidding which makes weak assumptions concerning the particular equilibrium being played in the auction and is robust across a wide range of bidding models. The assumption which enables them to impose this weak structure on the data is that at the end of an ascending auction, like the Simultaneous Ascending Auction used in the C block auction, a bidder's value from continuing the auction given their current bids must be at least as large as the values from submitting an alternate set of bids. These revealed preference restrictions are sufficient to identify the parameters of their structural model. To ascertain the importance of complementarities, they construct measures of the complementarities existing in a package of licenses, using more sophisticated measurements than the previously mentioned papers, and include them in the bidders' value functions. They then estimate their model using a two-sided matching estimator. They find that a one standard deviation increase in their complementarity proxy raises total package value by 33%.

The previously discussed papers seek to test for the *existence* of complementarities in an indirect fashion by testing for a link between submitted bids and variables thought to be related to complementarities. I proceed from an alternate direction. I seek to identify the complementarities directly by constructing a bidder's value function from submitted bid data. This allows me not only to directly test for the existence of complementarities in multi-good auctions, it also permits me to quantify those complementarities. This exercise presumes the existence of an accurate model of bidding behavior, which differs from the spirit of Haile and Tamer [19] and Bajari and Fox [5]. In these papers, the authors provide assumptions on bidder behavior which are likely to apply in a *wide range* of bidder behavior models. This frees their results from mis-specification concerns. However, when one uses a bidder behavior model, it enables a direct estimation of the bidder value function and the performance of counterfactual studies. This work contributes to the empirical auction literature as described in Athey and Haile [1].

I develop a model of bidding behavior in multi-unit, multi-good auctions by extending the framework in Wilson [33]. I model behavior in simultaneous uniform-price auctions. The model provides restrictions on bidder behavior, which I exploit to quantify the bidders' valuation functions. Since bidders in most "auctions in the wild" are limited to a discrete strategy space, I follow Nautz [29] and discretize the model. I extend the discrete model presented in Kang and Puller [24] to a multi-unit, multi-good case. The central theoretical object in Wilson's paper is the distribution of the uncertainty faced by the bidder, which is, namely, the location of the residual supply curve faced by the bidder that arises from bidders only observing their *private* signal and the distribution of other bidders' signals. I extend this object to the case of multiple, simultaneous auctions.

The bidder behavior model that I impose on the auction allows me to decompose behavior into strategic and cross good effects. The strategic effects arise from the uniform pricing rule. The cross good effects arise from the fact that the goods being auctioned are complements, therefore a bidder can value packages of these options more than the sum of the component values. I employ a discrete bidder behavior model to characterize solutions to the expected profit-maximizing problem. I use the restrictions of the model, along with a parametric value function assumption, to recover each bidder's value function from the set of bids that were submitted. To estimate this model, I provide a basis for identification of the bidder value functions. This proceeds from the fact that bidders are restricted to submitting price-quantity bids separately for each good. I provide a rationale that allows me to identify the bidders' multi-dimensional value functions. I also develop a resampling procedure to compute each bidder's expectations of market outcomes. These expectations are crucial to recovering value functions from bid data.

I use the estimated bidder value functions to estimate the efficiency of the simultaneous uniform price auction format relative to the first-best outcome. To do this, I first compute the socially optimal allocation. This optimal allocation would be achieved in the event that a direct revelation mechanism were available in this setting. I assume the existence of such a mechanism. This allows me to perform a counterfactual auction in which each bidder submits her value function to the auctioneer. I then maximize the efficiency of the auction by computing the allocation which maximizes bidder value. Hence, this efficiency measurement quantifies the benefit, in a particular setting, to developing such a mechanism.

The simultaneous uniform price auction achieves a low level of efficiency in this setting. This poor level of efficiency is driven by two opposing forces of bidding behavior. The first is market power possessed by some bidders. Market power causes bidders to reduce the amount that they demand in order to obtain a lower quantity of goods at a lower price. For some bidders this is the dominant effect. The other effect faced by bidders is related to the complementary nature of the goods being auctioned. This synergy effect causes bidders to increase their demand, and for some bidders this is the dominant force.

A. Electricity deregulation in Texas

The auctions that I analyze take place in the Texas electricity market. I analyze an auction for financial transmission rights in Texas. These financial transmission rights have an interdependent value structure, which is derived from the physical properties of how electricity is "transported" across an electricity grid. To see this more clearly, I will provide a brief institutional history of the electricity market in Texas. I then turn to a discussion of what financial transmission rights are and how they are implemented in the Texas electricity market.

The production, transmission and distribution of electricity in Texas has historically been regulated. This state of affairs was ensconced in the Public Utility Regulatory Act. The state Legislature voted to amend this Act in 1995 to allow for the deregulation of wholesale generation market in Texas.[6] In May 1999, the state Legislature further deregulated the Texas electricity market with the passage of Senate Bill 7, which instructed the Electric Reliability Council of Texas (ERCOT) to develop the necessary infrastructure to deregulate the retail electricity market as well.

Senate Bill 7 put ERCOT firmly at the center of electricity in Texas. ERCOT oversees the reliability of the power grid in Texas, runs centralized markets for power and facilitates retail competition. However, most electricity in the Texas electricity market is sold using bilateral contracts. The proportion averages around ninety-five percent. The prices and terms of these transactions are private information. This is in contrast to a centrally run, bid-based power pool that is used in several other deregulated electricity markets. While the terms of the contracts are confidential, the power flows that result are under ERCOT's purview.

Since most power is contracted for before demand is realized, there is inevitably a difference between what power producers planned to produce and what consumers actually demand. This difference is made up for in a "net-pool," or balancing energy market.[7] The balancing market is run every fifteen minutes. Market participants

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[6]This right falls to the state government, since the main electricity region of Texas is entirely within state lines. This turn of fate forbears the Federal Energy Regulatory Commission from regulating electricity transactions in Texas.

[7]Due to the nature of electricity, supply and demand must be equalized many

submit bids for marginal increases and decreases in the power output. In normal conditions there is one balancing energy market and one clearing price. Since the clearing price of the balancing market is the price for the last unit of electricity produced on the grid, it is often used as a proxy for the marginal price of electricity by market participants. In a competitive market, this price would represent the least cost unit.

In normal times the flow of electricity is unimpeded by the power grid. Departures from normality can occur for several reasons. If the ability of an element of a major transmission corridor to transmit power becomes diminished, zonal congestion is likely to occur. If a major power plant, such as one of the two nuclear power plants in Texas fails, zonal congestion would likely follow as power flows into either region to restore balance. Other reasons are weather related. High temperatures during the summers in Texas reduce the ability of transmission lines to transmit power. High summer temperatures also drive increased use of air conditioning. Taken together these two forces make zonal congestion more likely in the summer months. Market power can also lead to zonal congestion, but I will not discuss these scenarios here.

When zonal congestion occurs, ERCOT uses a model of the electricity grid to aid in altering the flow of power so that reliability is not compromised and, when possible, market mechanisms are employed in the process. ERCOT uses a model which divides the power grid into zones to manage transmission congestion.[8] In this model, there are groups of large transmission lines, or transmission corridors, that are deemed to

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times a second. Even small imbalances result in highly unstable conditions on the power grid.

[8]There are two different types of congestion deemed by ERCOT for congestion management purposes. I will focus on zonal congestion. Local congestion is another type in which ERCOT orders specific power units to change levels of production. This type of congestion occurs outside of market mechanisms and is not relevant to this research.

be the connections between these zones. ERCOT divides power plants and loads[9] into zones according to how they affect the flow of power on these transmission corridors. Power plants and loads in the same zone are deemed to have the same effect on each transmission corridor that connects zones.[10] The advantage of assuming an average effect allows resources and loads in the same zone to be regarded without respect to their location. This enables firms which own many power plants in the same zone to bid its units as a portfolio into the balancing energy market.

When there is transmission congestion between zones, ERCOT runs a balancing energy market for each zone. This division allows ERCOT to return power flows on congested transmission corridors to normal operating ranges using a market based mechanism. However, the division into smaller markets comes at a cost. In this situation there are multiple marginal units, and the marginal prices are necessarily higher than in the uncongested scenario. When this type of congestion occurs, ERCOT levies this cost upon market participants. Initially, ERCOT socialized these costs across market participants. This led to the use of a well known market manipulation technique known as the "dec" game. To carry out this game, a firm would schedule to produce an amount of power large enough to cause zonal congestion. In real time, when congestion occurred, ERCOT would alter power flows using market mechanisms. Cognizant of this fact, the firm would submit large bids in the balancing market to reduce its power output. The result of the game is the manipulating firm(s) being paid to resolve the zonal congestion that they created. The game is profitable when the costs of such behavior are levied across a large group of firms.

After the payments due to this manipulation reached an unacceptably high level,

[9]Sources of demand for electricity, either residential or industrial.

[10]There is error in assuming an average effect, but a discussion of the reasons and consequences of this is outside the scope of this research. See Baldick 2003

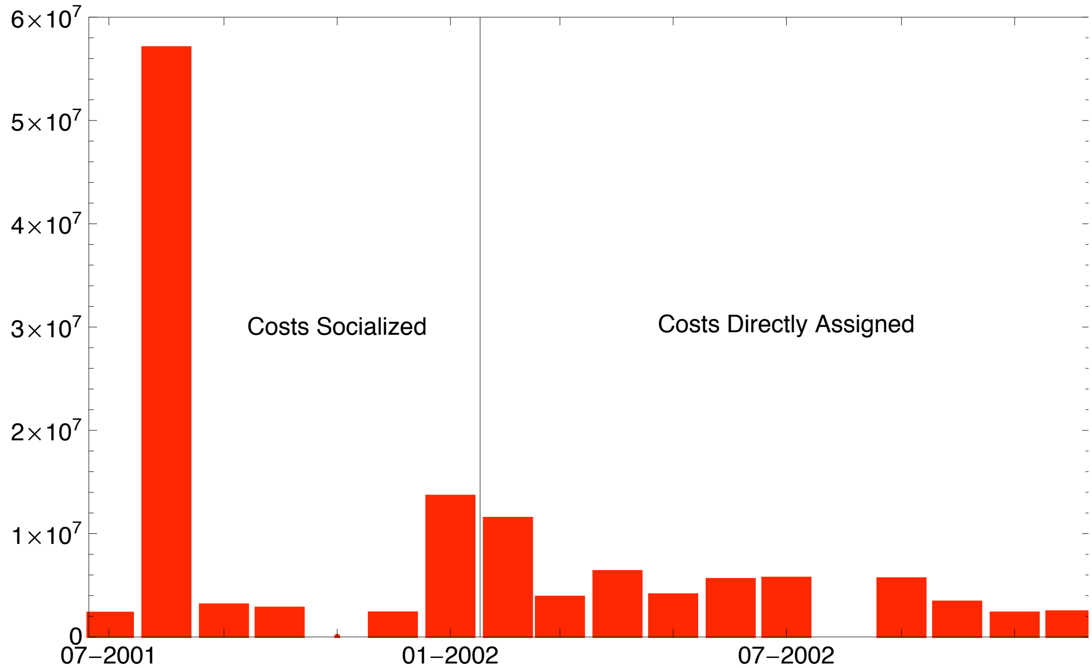


Fig. 1.: Total monthly zonal transmission costs in ERCOT before and after direct assignment of these costs occurred in February 2002.

ERCOT began to directly assign zonal congestion costs to the firms that caused. Figure 1 depicts monthly zonal congestion costs before and after this change occurred in February 2002. Once the costs of zonal congestion were directly assigned, firms required an instrument to hedge against them. This brought about the need for financial transmission rights in Texas. For a more in depth discussion of the developments and market mechanisms of ERCOT over this period, see Baldick and Niu [6].

B. Introduction to financial transmission rights

To illustrate the purpose and function of financial transmission rights in Texas, I will construct an example. Consider the case of an electricity grid with two zones

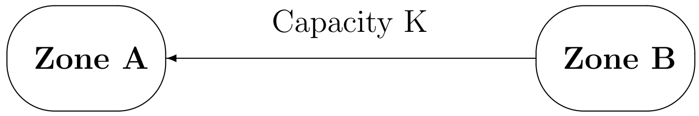


Fig. 2.: A two zone electricity grid with one transmission line connecting the zones.

depicted in Figure 2. In this example, Zone A has more expensive generation and has less generation than Zone B. Up to K units of power can flow from Zone B to Zone A. To determine the amount of power that actually flows between these zones, we need to consider costs. I will assume that the markets in both zones are competitive. If $K = K1$ as depicted in Figure 3, then sufficient production in Zone A can be avoided such that the marginal costs in both zones are equalized, and least-cost dispatch is achieved. The clearing price in both zones, since there is only one marginal unit, is equal to P_C.

When the capacity of the line, K, is less than $K1$, then least-cost dispatch cannot be achieved. This is depicted in Figure 3. In order to meet demand, the generators in this system must be redispatched. Generation in Zone A must be increased by $K1 - K$. Generation in Zone B must be decreased by $K1 - K$. This reallocation of production has an incremental cost $(P_A - P_B) \times (K1 - K)$ to implement. This increased cost is depicted as the rectangle labeled "Re-Dispatch Costs." In this scenario Zone A can import less power from Zone B than in the uncongested case. Since transmission capacity is scarce in this example, there are scarcity rents, often referred to as congestion rents. These rents are also depicted in Figure 3.

Congestion rents are returns that are generated when transmission is a scarce resource. In electricity markets it is often the case that these rents are auctioned. In auction parlance, shares of congestion rents are auctioned. In our example, there

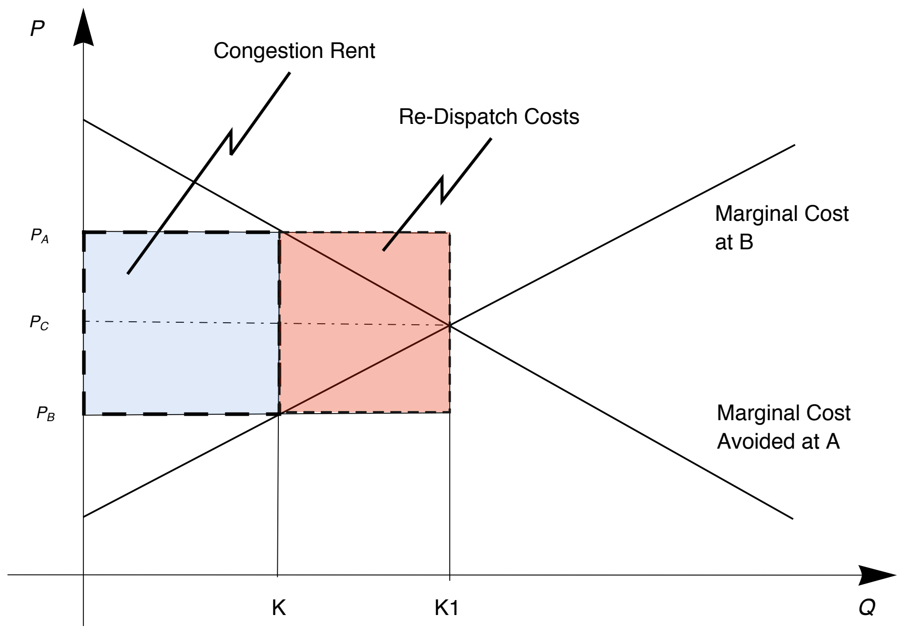


Fig. 3.: Congestion rents and redispatch costs in the two zone grid.

is only one transmission line that generates congestion rents. In ERCOT's zonal transmission model, there have historically been three to five transmission corridors whose congestion rents are auctioned. Shares of this revenue are referred to as financial transmission rights.[11] A holder of a financial transmission right owns a claim to a share of future congestion rents generated when a given transmission corridor is congested in a certain direction. A holder of a financial transmission right in my example would receive a share of the congestion rents generated when the capacity of the line from Zone B to Zone A is less than $K1$.

Financial transmission rights are purely a financial instrument. They are similar in nature to an option with a zero strike price. While it is customary for electricity

[11]Financial transmission rights are referred to as Transmission Congestion Rights in ERCOT. Since the former is a more widely used term in the literature, I will use this convention.

market firms to hold these rights, financial firms hold these rights as well. Electricity firms in ERCOT use these rights to hedge against zonal congestion costs, which were directly assigned to them starting in February 2002. Consequently, in 2002 ERCOT began auctioning financial transmission rights. In 2002 ERCOT used simultaneous uniform price auctions to allocate these rights.

When there are more than two zones, the valuation of financial transmission rights becomes intertwined. As will be discussed subsequently, when a firm enters into a transaction for power from one zone to another, power flows across all major transmission corridors. This results from the physics of power flow. Hence, to hedge against zonal congestion costs, a firm would need to acquire a *package* of financial transmission rights. As a result the value of one financial transmission right depends on how many other types of rights a firm owns. This interdependent value structure presents an impediment for simultaneous uniform price auctions, which are cleared independently, to achieve an efficient allocation.

The impediment of the initial auction format, the simultaneous uniform price used throughout 2002, was brought to market participants and as a result, a market revision which altered the auction format was ratified in May 2002.[12] The auction format was changed to a single-round, simultaneous combinatorial auction for all financial transmission rights available. This change was implemented in January 2003. A unique opportunity, however, presents itself from an empirical standpoint. Since it is known that a set of financial transmission rights has an interdependent value structure, this offers a natural experiment to ascertain how well simultaneous uniform price auctions perform in this setting. To that end I will develop a theoretical bidder behavior model and estimate the first order conditions using auction bid data

[12]The market revision was Protocol Revision Request 329.

from the simultaneous uniform price auctions that transpired in 2002.

I proceed as follows. In Chapter II, I present the model of bidder behavior and derive a discrete version of the model consistent with auctions in which bidders' strategy spaces are restricted to quantity and price grids. In Chapter III, I discuss the identification of the model and present the empirical methodology. In Chapter IV, I discuss the relevant institutional details for the financial transmission rights auctions which took place in 2002, the period of my data set. In Chapter V, I discuss the results of the application of the bidder behavior model to bid data for financial transmission rights and compute the efficiency of the multi-good, multi-unit uniform-price mechanism. In Chapter VI, I summarize my findings and indicate directions for future research.

CHAPTER II

BIDDER BEHAVIOR MODEL

In this chapter I will present a formal model of bidder behavior and characterize the equilibrium. The model builds upon work in single-good multi-unit auctions. The auctions for financial transmission rights in Texas were simultaneous, uniform-price auctions, in which the market for each type of right was cleared separately. Bidders submitted discrete price-quantity pairs for each type of right. The bids were collected by the auctioneer and each market was cleared separately. While each bidder submitted separate bid "functions" for each type of right, these bids were not contingent in any way across markets. Thus, given the interdependent valuation structure, bidders were forced to form expectations of market outcomes in each market. This important aspect of bidder behavior is reflected in my formal bidder behavior model. The interdependent valuation structure is modeled with a multivariate value function that maps a set of rights to a value. The market outcome of interest is the market clearing price. Bidders' expectations regarding market clearing prices are modeled as a joint distribution function.

I begin by modeling bidder behavior in a continuous setting. Since, the auction setting that I analyze is discrete, I develop a discrete model of bidder behavior. After developing the discrete model, I characterize the equilibrium of the auction and incorporate additional, *sine qua non* facets of the real world auction setting.

A. Bidder behavior model

I model the simultaneous, multi-unit, uniform price auctions as a static game of incomplete information. The model of bidding behavior is an extension of the seminal work of Wilson [33]. There are $N \geq 2$ bidders indexed by $i : \{1, \ldots, N\}$. N is known and common knowledge. There are M types of divisible goods, which are auctioned in M simultaneous uniform-price share auctions.[1] Each bidder receives a private signal, s_i, which can be a scalar or vector, that encapsulates the bidder's information about the underlying value of the goods being auctioned.

Assumption 1 (Distribution of Signals) *Bidder i's signal is drawn from a common support* $[\underline{s}, \overline{s}]$ *according to an atomless marginal distribution function* $F_i(s_i)$ *with a strictly positive density function* $f_i(s_i)$

The joint distribution of the bidders' signals is $F(s)$. Bidders win a vector quantity of goods $\boldsymbol{q} \in [0,1]^M \ \forall m \in \{1, \ldots, M\}$ or $\boldsymbol{q} = [q_1, \ldots, q_M]$, where $q_m \in [0,1]$. Let $V : [0,1]^M \to \mathbb{R}$ be defined as the bidder value function, which denotes bidder i's value for a particular set of goods. Bidder i's gross utility from winning $\boldsymbol{q}$ units of each good is $V_i(\boldsymbol{q}, s_i, s_{-i})$.

Assumption 2 (Value Function Properties) *I will assume the following about the value function:*

1. *Bidder i's value function is twice differentiable.*
2. *Bidder i's value function is strictly increasing in* $\boldsymbol{q}$ $\forall$ (s_i, s_{-i}). *Therefore,* $\forall\, \boldsymbol{q}^A, \boldsymbol{q}^B \in Q^M : q_i^A > q_i^B$ *for some* $i \in \{1, \ldots, M\}$, *then* $V(q^A) > V(q^B)$.
3. *Furthermore,* $V(\mathbf{0}) = 0$.

I will restrict the analysis to the special case of independent private values (IPV) in which bidders' signals are identically and independently distributed across bidders. This is a reasonable assumption in this setting, since each bidder's value depends on

[1] In reality there are Q^m units of good m available. Q^m is known and common knowledge. However, I will normalize quantities to lie on the interval $[0,1]$.

private information concerning its contract positions in the electricity market. This restriction reduces the value function to $V(\boldsymbol{q}, s_i)$. Bidder i's utility function is defined over vectors of goods in Q^M and wealth, w:

$$U_i(\boldsymbol{q}, w, s_i) = V_i(\boldsymbol{q}, s_i) + w \tag{2.1}$$

Bidders seek to maximize their expected utilities by choosing a pure strategy, σ_i, which maps the bidder's private signal to the set of bid functions. I will restrict the bid functions, following Wilson [33], to the set $\mathcal{Y}$ which is the set of all strictly decreasing, differentiable functions $y : \mathbb{R}_+^M \rightarrow [0,1]^M$.[2] Hence the bidders' pure strategies are $\sigma_i : S_i \rightarrow \mathcal{Y}$. For a bidder of type s_i, the bid function is $y_i(\boldsymbol{p}|s_i)$, which specifies for each vector of prices, $\boldsymbol{p}$, what share of each of the M goods being auctioned bidder i demands.

Let there be Q^m units of good m available. This quantity is assumed to be commonly known before the auction occurs. The bidders submit demand functions to the auctioneer for each good. The auctioneer then creates an aggregate demand curve for each good and intersects this with its corresponding supply curve, resulting in a market clearing price for each good. An equivalent method for computing the market clearing vector of prices, $\boldsymbol{p}^c$, occurs when bidder i's demand curve intersects her residual supply curve in each market:

$$y_i^m(\boldsymbol{p}^c|s_i) = Q^m - \sum_{j \neq i}^{N} y_j^m(\boldsymbol{p}^c|s_j), \ \forall \, m \in M. \tag{2.2}$$

When formulating her strategy, bidder i faces uncertainty with respect to the location of the residual supply curves, and hence the market clearing price, for each

[2]Here the signal is a positive, real scalar. I can generalize this to the case where the signal is a vector.

good, since she only knows her signal, s_i and not the signals of her rivals, s_j where $j \neq i$. Bidder i must form expectations concerning the location of these curves, which she can do conditional on her demand curve and her realized signal. Extending Wilson [33], I define:

$$\begin{aligned} H(p_1, \ldots, p_M | y_i(\boldsymbol{p}|s_i)) &= \Pr\big\{ y_i(\boldsymbol{p}|s_i) \leq \boldsymbol{Q} - \sum_{j \neq i}^{N} y_j(\boldsymbol{p}|s_j) \big\} \\ &= \Pr\big\{ \boldsymbol{p}^c \leq \boldsymbol{p} \,|\, y_i(\boldsymbol{p}|s_i) \big\}, \end{aligned} \tag{2.3}$$

where $\boldsymbol{Q}$ is a vector containing the number of units available of each type of good, $\boldsymbol{p}^c$ is a vector of market clearing prices and $\boldsymbol{p}$ is a vector of prices. Hence, $H(p_1, \ldots, p_M | y_i(\boldsymbol{p}|s_i))$ is the probability of the joint events $\{p_1^c \leq p_1, \ldots, p_M^c \leq p_M\}$ occurring, conditional on bidder i submitting the bid function $y_i(\boldsymbol{p}|s_i)$. For a given p and $y_i(\boldsymbol{p}|s_i)$, $H(\cdot)$ is a probability distribution function, which I assume is differentiable in p and $y(\boldsymbol{p}|s_i)$. I can now construct the model of bidder behavior.

I use the Bayesian Nash solution concept. The expected utility of a type s_i of bidder i, who submits the bid function $y_i(\boldsymbol{p}|s_i)$ given that the $j \neq i$ bidders submit $\{y_j(\boldsymbol{p}|s_j)\}$ is:

$$\begin{aligned} EU_i(s_i) &= E_{\boldsymbol{Q}, s_{-i}|s_i} u(s_i) \\ &= E_{\boldsymbol{Q}, s_{-i}|s_i} \left\{ \int_0^\infty \big[V(y(\boldsymbol{p}^c|s_i), s_i) - \boldsymbol{p}^c \cdot y_i(\boldsymbol{p}^c|s_i) \big] dH(p_1^c, \ldots, p_M^c \,|\, y_i(\boldsymbol{p}^c|s_i)) \right\}, \end{aligned} \tag{2.4}$$

where $\boldsymbol{p}^c$ is defined as in equation (2.2). A Bayesian Nash Equilibrium is a collection of functions such that almost every type s_i of bidder i submits a bid function which maximizes her expected utility by solving the succeeding problem:

$$\max_{y_i(\cdot|\cdot)\in\mathcal{Y}} \int_0^\infty \big[V(y(\boldsymbol{p}^c|s_i), s_i) - \boldsymbol{p}^c \cdot y_i(\boldsymbol{p}^c|s_i)\big]\, dH(p_1^c, \ldots, p_M^c | y_i(\boldsymbol{p}^c|s_i)) \qquad (2.5)$$

The necessary condition of equation (2.5) implicitly defines a type dependent bid function which is a pure strategy of the form σ_i. These strategies can establish a Bayesian Nash Equilibrium.[3] However, there are likely to be a multitude of equilibria. This does not create a problem for me, since the previously discussed bidding model characterizes *any* equilibria which might occur. Since the auctions that I analyze take place in a discrete setting, I will proceed with the development of a discrete version of the preceding continuous formulation.

In the vast majority of real world auctions, there are restrictions on the bidders' strategy space which constrain bidders to a discrete strategy space. For example, prices are often quoted in dollars of which the smallest unit is one-hundreth of a dollar. On the quantity side, there is almost always a discrete amount of goods available, which is at odds with the divisible goods model derived previously. Combining these discrete price and quantity restrictions, the bidders' strategy space for one good is a discrete two-dimensional grid. In addition, in some auctions bidders are limited to some maximum number of bidpoints. Therefore, it is appropriate for me to derive a discrete version of the bidder behavior model. I follow Nautz [29], Hortaçsu [22] and Kang and Puller [24] in developing the discrete model.

The prices for good m are restricted to lie on a discrete grid. Let $p_{m,0} \leq p_{m,1} \leq \cdots \leq p_{m,J^m} \leq p_{m,J^m+1}$ be the price grid for good m. There are $J^m + 2$ points on the price grid for good m, and j_m is an index for good m. The difference between

[3] There is no proof of existence for a group of simultaneous auctions of this form in the literature. However, Bikhchandani [7] proves the existence of an equilibrium in the case in which there are simultaneous auctions *for each* good. In this case there would be $\sum Q^m$ auctions as opposed to the M auctions which I study.

prices on the grid for good m is constant, $|p_{m,i} - p_{m,j}| = \Delta_{m,p}$ for every $i \neq j$. This difference and the size of the grid are not restricted to be equal across goods. A bid vector is a series of quantities corresponding to the quantity demanded at each price point: $\vec{y}_m = \{y_{m,0} \geq y_{m,1} \geq \cdots \geq y_{m,J^m} \geq y_{m,J^m+1}\}$. I will assume that $y_{m,J^m+1} = 0$, and that the probability of the market clearing at price $p_{m,0}$ is equal to zero for all $m \in M$. Bidders submit a vector valued function for each good m, conditional on the signal they receive, which will be denoted as $\vec{y_i}^{\,m}(s_i)$. The bid "function" for all goods is defined as $\vec{\boldsymbol{y}}_i(s_i)$.

To clear each market, the auctioneer aggregates the bids and finds the prices at which aggregate demand narrowly fails to exceed aggregate supply. For good m this is:

$$p_{m,j^*_m} : j^*_m = \min\{j : \sum_{i=1}^{N} y^m_{ij} \leq Q^m\} \tag{2.6}$$

where y^m_{ij} is the quantity demanded by bidder i of good m at price $p_{m,j}$.

The distribution of the market clearing price in all markets can be constructed for bidder i as a joint probability function, *conditional* on bidder i's bid vectors: $H_i(p_{1,j_1}, \ldots, p_{M,j_M}; \vec{\boldsymbol{y}}_i(s_i))$, which is defined as the probability that $p_{m,j^*_m} \leq p_{m,j_m}$ for all m. I must define the marginal distributions of H for bidder i with respect to price p_m: $H_{p_m,i}(p_{1,j_1}, \ldots, p_{M,j_M}, \vec{\boldsymbol{y}}_i(s_i))$, which are equal to:

$$H_{p_m,i}(p_{1,j_1}, \ldots, p_{M,j_M}, \vec{\boldsymbol{y}}_i(s_i)) = \sum_{p_m \in \mathcal{A}_m} H_i(p_{1,j_1}, \ldots, p_{M,j_M}, \vec{\boldsymbol{y}}_i(s_i)) \tag{2.7}$$

I must also define the conditional probability distributions: $H_i(\boldsymbol{p}_{\wr}|p_m, \vec{\boldsymbol{y}}_i(s_i))$, where $\boldsymbol{p}_{\wr} \equiv \{p_{1,j_1}, \ldots, p_{\bar{M},j_{\bar{M}}}, p_{m+1,j_{m+1}}, \ldots, p_{M,j_M}\}$, which is defined as:

$$H_i(\boldsymbol{p}_{\wr}|p_m, \vec{\boldsymbol{y}}_i(s_i)) = \frac{H_i(p_{1,j_1}, \ldots, p_{M,j_M}, \vec{\boldsymbol{y}}_i(s_i))}{H_{p_m,i}(p_{1,j_1}, \ldots, p_{M,j_M}, \vec{\boldsymbol{y}}_i(s_i))} \tag{2.8}$$

Now I can construct the discrete version of the bidder's maximization problem for M goods. The problem below is the discrete version of equation (2.5), hence it is a computation of the expected value of the auction outcome for bidder i. Note that I am not restricting the prices across markets to be independent. This requires the use of conditional expectations throughout.

$$
\begin{aligned}
\max_{\{y_{m,j_m}\}} & \sum_{j_1=1}^{J^1+1} \left\{ H_{p_1}(p_{1,j_1}, \vec{\boldsymbol{y}}(s_i)) - H_{p_1}(p_{1,j_1-1}, \vec{\boldsymbol{y}}(s_i)) \right\} \times \\
& \left[\sum_{j_2=1}^{J^2+1} \left\{ H(p_{2,j_2}|p_{1,j_1}, \vec{\boldsymbol{y}}(s_i)) - H(p_{2,j_2-1}|p_{1,j_1}, \vec{\boldsymbol{y}}(s_i)) \right\} \times \cdots \times \right. \\
& \sum_{j_M=1}^{J^M+1} \left\{ H(p_{M,j_M}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) - \right. \\
& \quad \left. H(p_{M,j_{M-1}}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) \int_0^{y_{1,j_1}} V_{y_1}(q, \boldsymbol{y}_{-1}, s_i) dq - p_{1,j_1} y_{1,j_1} \right] \\
& + \cdots + \qquad\qquad (2.9) \\
& \sum_{j_M=1}^{J^M+1} \left\{ H_{p_M}(p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) - H_{p_M}(p_{M,j_M-1}, \vec{\boldsymbol{y}}(s_i)) \right\} \times \\
& \left[\sum_{j_1=1}^{J^1+1} \left\{ H(p_{1,j_1}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) - H(p_{1,j_1-1}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) \right\} \times \cdots \times \right. \\
& \sum_{j_{\bar{M}}=1}^{J^{\bar{M}}+1} \left\{ H(p_{\bar{M}}, j_{\bar{M}}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) - \right. \\
& \quad \left. H(p_{\bar{M},j_{\bar{M}}-1}|p_{M,j_M}, \vec{\boldsymbol{y}}(s_i)) \int_0^{y_{M,j_M}} V_{y_M}(q, \boldsymbol{y}_{-M}, s_i) dq - p_{M,j_M} y_{M,j_M} \right]
\end{aligned}
$$

Where I have the following notation:

$$V_{y_m}(q, \boldsymbol{y}_{-m}, s_i) = V_{y_m}(y_{1,j_1}, \ldots, y_{m-1,j_{m-1}}, q, y_{m+1,j_{m+1}}, \ldots, y_{M,jM}, s_i) \qquad (2.10)$$

$$\bar{M} = M - 1 \qquad (2.11)$$

Equation (2.9) is the general, discrete bidder maximization problem with m goods. The problem contains m groupings which involve computing the expected value of bidding J^m bid points for good m. To compute this expected value the bidder must iterate over the $\sum_{l \neq m} J^l$ bids for goods $l \neq m$. Since the bidder's value function is super-additive, the bidder takes into account what she will win for the other $M-1$ goods. Winning different amounts of these goods shifts the marginal valuation of good m. Hence, the bidder must compute the probability of each possible location of her marginal valuation of good m and then multiply it by the value she receives by winning this bundle of goods. With $\sum_m J^m$ bids, the bidder must iterate over $\Pi_m J^m$ possible bundles to determine the expected value of the auction outcome. To more clearly see these interactions, I will restrict $M = 2$.

To derive the necessary condition, I formulate the bidder optimization problem using the method of Lagrange. I include a monotonicity constraint on the bidder that restricts the bidder to submitting a weakly decreasing set of bid quantities in each market. Assuming that the monotonicity constraints are not binding, $\lambda^1_{j_1} = 0, \forall j_1 \in J^1$ and $\lambda^2_{j_2} = 0, \forall j_2 \in J^2$, I arrive at the following necessary condition for each bid point. Note that all distributions of the market clearing price are conditional on bidder i's bid functions. I suppress them for notational brevity.

$$
\begin{aligned}
&\sum_{j_2=1}^{J^2+1}\Big(\big[H(p_{1,j_1},p_{2,j_2})-H(p_{1,j_1-1},p_{2,j_2})\big]- \\
&\qquad\big[H(p_{1,j_1},p_{2,j_2-1})-H(p_{1,j_1-1},p_{2,j_2-1})\big]\Big)V_{y_1}(y_{1,j_1},y2,j_2,s_i)+ \\
&\sum_{j_2=1}^{J^2}\big(H(p_{1,j_1},p_{2,j_2})-H(p_{1,j_1-1},p_{2,j_2})\big)\int_{y_{2,j_2+1}}^{y_{2,j_2}}V_{y_2y_1}(y_{1,j_1},q)dq=
\end{aligned}
$$

$$
\begin{aligned}
&\big(H_{p_1}(p_{1,j_1})-H_{p_1}(p_{1,j_1-1})\big)p_{1,j_1}- \\
&\left(\begin{aligned}
&\frac{\partial H_{p_1}(p_{1,j_1})}{\partial y_{1,j_1}}\Bigg(\Bigg[\sum_{j_2=1}^{J^2+1}\big(H(p_{2,j_2}|p_{1,j_1})-H(p_{2,j_2-1}|p_{1,j_1})\big)\int_{y_{1,j_1+1}}^{y_{1,j_1}}V_{y_1}(q,y_{2,j_2})dq\Bigg] \\
&\qquad -p_{1,j_1}y_{1,j_1}+p_{1,j_1+1}y_{1,j_1+1}\Bigg)+ \\
&\sum_{j_2=1}^{J^2+1}H_{p_1}(p_{1,j_1})\left(\frac{H(p_{2,j_2}|p_{1,j_1})}{\partial y_{1,j_1}}-\frac{H(p_{2,j_2-1}|p_{1,j_1})}{\partial y_{1,j_1}}\right)\int_{y_{1,j_1+1}}^{y_{1,j_1}}V_{y_1}(q,y_{2,j_2})dq+ \\
&\sum_{j_2=1}^{J^2}H_{p_2}(p_{2,j_2})\frac{H(p_{1,j_1}|p_{2,j_2})}{\partial y_{1,j_1}}\int_{y_{2,j_2+1}}^{y_{2,j_2}}\big(V_{y_2}(y_{1,j_1},q)-V_{y_2}(y_{1,j_1+1},q)\big)dq
\end{aligned}\right)
\end{aligned}
\tag{2.12}
$$

Equation (2.12) collapses to the necessary condition derived in Kang and Puller [24] when good one and good two are not complementary. Thus, this necessary condition contains their formulation as a special case. The terms of this necessary condition provide a window into the forces that drive bidder behavior. There are market power effects and synergy effects which oppose each other. The market power effects drive bidders to shade their bid prices, while the synergy effects drive bidders to increase their bid prices.

In the two good case, the bidder must only consider the effects that good one has on good two and the effects that good two has on good one, along with the own good effects. First consider the market power effects that emerge when a bidder changes a particular bid quantity on the margin. This change has an effect on the probability distribution of the market clearing price for *both* goods. This marginal increase causes a marginal decrease in the probability that the market clearing price is less than the bid price, which corresponds to the particular bid in question. This result is akin to textbook comparative statics with supply and demand curves. Marginally increasing a bid quantity, marginally increases the demand at the bid price. This shift outwards moves more of the demand curve to a higher price, thus increasing the chances that the clearing price is higher. The ability to move the distribution of clearing prices is the market power possessed by the bidder. The stronger this ability, the more incentive a bidder has to engage in demand reduction. Market power here is derived from the fact that the bidder acts like a monopsonist on residual supply.

The second effect concerns the interdependent valuation of goods one and two, referred to as the synergy effects. By marginally increasing a bid quantity, a bidder affects the marginal valuations for both goods. A marginal increase in a bid for good one results in a greater own good valuation, but it also changes the marginal valuation for good two. When the bidder marginally increases a particular bid for good one and increases the expected winnings of good one, and the goods are complementary, the marginal valuation of good two increases. This marginal increase will result in an increase in the value of all the combinations of goods that contain this amount of (marginally increased) good one. If the goods are substitutes, then this effect will be exactly opposite and those combinations of goods will decrease. If the goods are ordinary goods, then this effect will be zero.

Since the bidder faces uncertainty concerning the actual allocation of goods she will receive, the bidder must form expectations over these outcomes. In order to demonstrate these effects, consider the case when the bidders are assumed to behave competitively. The first order condition under this assumption is:

$$\frac{1}{\big(H_{p_1}(p_{1,j_1}) - H_{p_1}(p_{1,j_1-1})\big)} \sum_{j_2=1}^{J^2+1} \Big(\big[H(p_{1,j_1}, p_{2,j_2}) - H(p_{1,j_1-1}, p_{2,j_2})\big] -$$
$$\big[H(p_{1,j_1}, p_{2,j_2-1}) - H(p_{1,j_1-1}, p_{2,j_2-1})\big]\Big) V_{y_1}(y_{1,j_1}, y_{2,j_2}, s_i) +$$
$$\frac{\sum_{j_2=1}^{J^2} \big(H(p_{1,j_1}, p_{2,j_2}) - H(p_{1,j_1-1}, p_{2,j_2})\big)}{\big(H_{p_1}(p_{1,j_1}) - H_{p_1}(p_{1,j_1-1})\big)} \int_{y_{2,j_2+1}}^{y_{2,j_2}} V_{y_2 y_1}(y_{1,j_1}, q) dq = \tag{2.13}$$
$$p_{1,j_1}.$$

In this case, the bidder equates bid price, marginal cost, and the expected marginal benefit. The expected marginal benefit is comprised of the expected marginal valuation of good one and the cross good effect that good one has on good two. For explanatory purposes, I simplify Equation 2.13:

$$\Omega_0 \sum_{j_2=1}^{J^2+1} \Omega_{1,j_2} V_{y_1}(y_{1,j_1}, y_{2,j_2}, s_i) + \Omega_0 \sum_{j_2=1}^{J^2} \Omega_{2,j_2} \int_{y_{2,j_2+1}}^{y_{2,j_2}} V_{y_2 y_1}(y_{1,j_1}, q) dq = p_{1,j_1} \tag{2.14}$$

Here we can see the process of computing the expected marginal valuation more clearly. Since the bidder does not know how much of good two she will possess when she is formulating a bid for good one, she is uncertain about the location of the marginal value curve for good one. Therefore, the bidder computes an expectation of its location. The first component of the left hand side in Equation 2.14 is the own good marginal value for good one. This sum holds the amount of good one constant at y_{1,j_1} and varies the amount of good two. Thus, it computes the expected own good marginal value. The second component of the left hand side in Equation 2.14 is the cross good marginal valuation. Again, the quantity of good one is held constant at

y_{1,j_1}, and the amount of good two is varied. The result being the expected value of the cross good effect. These two expected value components are equated with the bid price.

The greater the synergy effect, or cross good effect, the greater the incentive the bidder has to increase her bid price. Hence, market power and synergy effects ultimately determine the nature of bidder behavior.

B. Bidder behavior under a revenue returning mechanism

I must introduce one additional feature to the bidder behavior model that is seen in some auctions. For a myriad of reasons, there are situations where the auctioneer must remain revenue neutral. This requires that the auctioneer make a series of payments equal in sum to the payments made to the auctioneer to a set of firms that is not necessarily the set of firms who participated in the auction. How this revenue is returned can impact bidder behavior. In the auctions that I analyze, the auction revenues were distributed to a set of firms that included a subset of the bidders. To more accurately model bidder behavior, these payments to bidders must be included in the analysis. This aspect of auctions has been considered in auction theory since the seminal work of Vikrey.

The method by which auction revenues are returned to firms is assumed to be exogenously determined by the auctioneer and is *ex ante* common knowledge. However, the amount of auction revenue is endogenously determined by bidder behavior. Therefore, the inclusion of auction revenues does affect the expected profits of the auction. The set of firms to which auction revenues are returned is Ψ. Some firms in Ψ participate in the auction, and others do not. Hence, I will assume that the set of bidders, N, includes two, disjoint subsets. One subset includes bidders that receive a share of auction revenue and is denoted ζ. The other, ν, includes bidders that do not receive a share of auction revenue. Furthermore, I will assume that $\zeta \subseteq \Psi$. Auction revenues are returned to the set of firms in Ψ according to the function $R(\boldsymbol{p}^c, \boldsymbol{Q}, \Psi, \rho_k)$, where $\boldsymbol{p}^c$ is the vector of market clearing prices, $\boldsymbol{Q}$ is the vector of the quantity of each type of good auctioned, Ψ is the set of firms to which revenue is returned, and ρ_k is the percentage of auction revenues that firm k receives. By construction, $\sum \rho_k = 1$. Including this function in the expected profits of bidders' results in the following expected profit maximization problem.

$$\max_{y_i(\cdot|\cdot)\in\mathcal{Y}} \int_0^\infty \big[V(y(\boldsymbol{p}^c|s_i), s_i) - \boldsymbol{p}^c \cdot y_i(\boldsymbol{p}^c|s_i) + R(\boldsymbol{p}^c, \boldsymbol{Q}, \Psi, \rho_i)\big]\, dH(p_1^c, \ldots, p_M^c|y_i(\boldsymbol{p}^c|s_i)) \tag{2.15}$$

Since $\boldsymbol{Q}$, Ψ and ρ_i are exogenously determined, the unique method for a bidder to affect the amount of auction revenues it receives is by altering the distribution of market clearing prices. The avenue by which a bidder achieves this is varying the quantities that she bids. By increasing the bid quantity on the margin and holding the corresponding bid price fixed, a bidder decreases the probability that the market clearing price is less than the corresponding bid price. This marginal increase in bid quantity raises the expected auction revenues. The bidder must balance this increase in expected returned revenues with the increase in the expected amount the bidder would pay for any acquired goods.

Returning revenue to a subset, ζ, of bidders subsidizes their purchase of goods being auctioned. While this will increase these bidders' valuations, the increase is purely financial and orthogonal to the goods being auctioned *per se*. The nature of the revenue return function, $R(\boldsymbol{p}^c, \boldsymbol{Q}, \Psi, \rho_k)$, will determine whether or not this aspect of the auction impacts efficiency through altering bidders' incentives. One possible manifestation could be that bidders in ζ, who receive revenue, have on average lower valuations for the goods being auctioned than bidders in ν, who do not receive revenue. Since receiving auction revenue reduces the marginal expenditure of bidders in ζ, they will tend to increase the quantities that they bid for given prices which would result in these bidders procuring a higher share of the auctioned goods.

To derive the necessary condition under this new regime, I formulate the bidder optimization problem using the method of Lagrange. I retain all assumptions imposed in the previously derived necessary condition.

$$\sum_{j_2=1}^{J^2+1}\Big(\big[H(p_{1,j_1},p_{2,j_2})-H(p_{1,j_1-1},p_{2,j_2})\big]-$$
$$\big[H(p_{1,j_1},p_{2,j_2-1})-H(p_{1,j_1-1},p_{2,j_2-1})\big]\Big)V_{y_1}(y_{1,j_1},y2,j_2,s_i)+$$
$$\sum_{j_2=1}^{J^2}\big(H(p_{1,j_1},p_{2,j_2})-H(p_{1,j_1-1},p_{2,j_2})\big)\int_{y_{2,j_2+1}}^{y_{2,j_2}}V_{y_2y_1}(y_{1,j_1},q)dq=$$

$$\begin{gathered}\big(H_{p_1}(p_{1,j_1})-H_{p_1}(p_{1,j_1-1})\big)p_{1,j_1}- \\ \left(\begin{aligned}&\frac{\partial H_{p_1}(p_{1,j_1})}{\partial y_{1,j_1}}\Bigg(\Bigg[\sum_{j_2=1}^{J^2+1}\big(H(p_{2,j_2}|p_{1,j_1})-H(p_{2,j_2-1}|p_{1,j_1})\big)\int_{y_{1,j_1+1}}^{y_{1,j_1}}V_{y_1}(q,y_{2,j_2})dq\Bigg] \\ &\qquad -p_{1,j_1}y_{1,j_1}+p_{1,j_1+1}y_{1,j_1+1}+R(p_1^c,Q_1,\Psi,\rho_i)\Bigg)+ \\ &\sum_{j_2=1}^{J^2+1}H_{p_1}(p_{1,j_1})\left(\frac{H(p_{2,j_2}|p_{1,j_1})}{\partial y_{1,j_1}}-\frac{H(p_{2,j_2-1}|p_{1,j_1})}{\partial y_{1,j_1}}\right)\int_{y_{1,j_1+1}}^{y_{1,j_1}}V_{y_1}(q,y_{2,j_2})dq+ \\ &\sum_{j_2=1}^{J^2}H_{p_2}(p_{2,j_2})\frac{H(p_{1,j_1}|p_{2,j_2})}{\partial y_{1,j_1}}\int_{y_{2,j_2+1}}^{y_{2,j_2}}\big(V_{y_2}(y_{1,j_1},q)-V_{y_2}(y_{1,j_1+1},q)\big)dq\end{aligned}\right)\end{gathered} \tag{2.16}$$

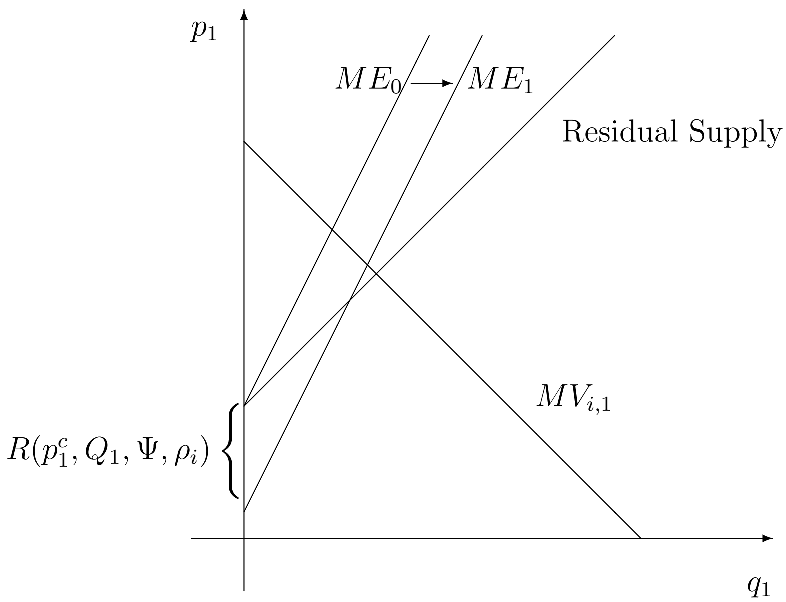


Fig. 4.: Graphical depiction of the effects of returning revenue to a bidder on the marginal expenditure function.

The revenue return function appears once in equation (2.16) in the market power term. To better understand the effect of this inclusion on bidder behavior, I will construct an illustrative example, which is depicted graphically in Figure 4. Suppose that the uncertainty surrounding the bid functions for all $j \in N$, $j \neq i$ is resolved. Bidder i can monopsonize a singular residual supply curve. In the absence of revenue return, bidder i has a marginal expenditure function that is twice the slope of the residual supply curve. When revenue return is added, the marginal expenditure shifts to the right in accordance with the amount of revenue the bidder receives. Thus, returning revenue increases demand via an increase in the “value” of the goods through, in effect, a subsidy of their purchase.

CHAPTER III

EMPIRICAL BIDDER BEHAVIOR MODEL AND ESTIMATION

This chapter will lay out the empirical bidder behavior model, discuss identification of the model and present the estimation procedure. I now proceed with a discussion of the empirical aspects which arise in taking the theoretical model to auction bid data. I first discuss the identification of the theoretical model. There are two identification issues that must be addressed. First, I must identify the joint probability distributions of market clearing prices. Second, I must offer evidence that I can identify a multidimensional value function from price, quantity demanded pairs that are submitted for each of the M goods being auctioned. After I discuss identification, I describe the estimation of the model. There are four steps to the estimation procedure. First, I estimate the joint distributions of market clearing prices for each bidder using a bootstrap procedure. Second, I compute each bidder's first order conditions assuming a parametric value function. Third, I recover the parameters of each bidder's value function that best fit their first order conditions. Fourth, I carry out a counterfactual auction to assess the efficiency of the actual auction.

A. Identification of the model

In order to identify the bidders' valuation functions I follow the tact taken in Elyakime et al. [13] and Guerre et al. [17] who exploit the necessary condition which characterizes the optimal bid function in a first-price sealed-bid auction to identify the bidders' marginal valuations. Hortaçsu [22] and Kang and Puller [24] follow this approach for a discriminatory multi-unit auction and a uniform-price multi-unit auction, respectively. However, in this literature, because they worked in a single good environment, the necessary condition was sufficient to identify the bidders' marginal valuations. In a single-good case, assuming the bid functions were generated by a Bayesian Nash Equilibrium, one is able to non-parametrically identify bidders' marginal valuations in the following manner. Follow Hortaçsu [22], define the probability that at price p the demand of quantity x is less than the stochastic residual supply faced by bidder i as:

$$G_i(p,x) = Pr\left\{x \leq Q - \sum_{j \neq i}^{N} y(p,s_j)\right\} \tag{3.1}$$

If I can estimate the joint distribution of $\{y(p,s_j), j \neq i\}$, I can estimate this probability for all price, quantity demanded pairs. Then,

$$H(p, y(p,s_i)) = G(p,x)|_{x=y(p,s_i)} \tag{3.2}$$

$$\frac{\partial}{\partial p} H(p, y(p,s_i)) = \frac{\partial}{\partial p} G(p,x)|_{x=y(p,s_i)} \tag{3.3}$$

In Hortaçsu [22], the first order condition maps each bid to a point on the marginal value function. Given equations (3.2) and (3.3), Hortaçsu [22] achieves a non-parametric identification of the bounds of each bidder's marginal value function.[1]

In a multi-good setting, one cannot achieve this non-parametric identification of the bidder marginal value functions, which will be discussed below. However, in this setting I can follow a similar approach to construct the joint distributions of market clearing prices by defining the probability that x^m is less than the stochastic residual demand for good m for all $m \in \{1, \ldots, M\}$ as,

[1] See Equation (6) in Hortaçsu [22].

$$G(p_1, \ldots, p_M, x_1, \ldots, x_M) = Pr\Big\{x_m \leq Q^m - \sum_{j \neq i}^{N} y^m(p_m, s_j)\; \forall\, m \in \{1, \ldots, M\}\Big\} \tag{3.4}$$

I can then estimate $G(\cdot)$ if I can compute the joint distribution of $\{y^m(p_m, s_j),$ $j \neq i, \forall\, m\}$ for all price, quantity-demanded pairs $(p_m, x_m)\,\forall\, m$ in the data. I now define:

$$H_i(\boldsymbol{p}, y(\boldsymbol{p}, s_i)) = G_i(\boldsymbol{p}, \boldsymbol{x})|_{x_1 = y^1(p_1, s_i), \ldots, x_M = y^M(p_M, s_i)} \tag{3.5}$$

$$\frac{\partial}{\partial p_m} H_i(\boldsymbol{p}, y(\boldsymbol{p}, s_i)) = \frac{\partial}{\partial p_m} G_i(\boldsymbol{p}, \boldsymbol{x})|_{x_1 = y^1(p_1, s_i), \ldots, x_M = y^M(p_M, s_i)} \tag{3.6}$$

where $m \in \{1, \ldots, M\}$. Hence, assuming that each submitted price, quantity demanded pair arises out of a Bayesian Nash Equilibrium, I can compute the joint distribution of market clearing prices for each bidder.

I now turn to the identification of the bidder value functions. The issue that arises in a multi-good case is whether there is enough information from a set of bid functions, where each bid function is a step bid function for *one* good, to identify a multi-dimensional value function. If each bid in one market contains the same information about goods in other markets, there would not be enough information to identify the nature of cross-good effects. What is required, then, is that when submitting bids for one good, the bidder expects to win differing amounts of the other goods.

In more technical terms, I need to resolve whether I can use lower dimensional bid functions to identify a higher order value function. I observe bidders submitting discrete bid functions for M goods. In what cases can I use these bid functions to identify the multidimensional value function? I see multiple price-quantity pairs for each good for each bidder. In order to identify the multidimensional value function, I need to use information contained in these bids to recover own-good and cross-good valuations. For example, when a bidder submits an additional bid point for one good, does this offer any additional information concerning how the bidder's valuation of this good changes with respect to the other goods being auctioned? I will consider three cases. In all three cases, identification requires that bidders submit bids from continuous demand functions that arise out of a Bayesian Nash Equilibrium of the auction game. In the case of ordinary goods, the value function is additive and identification is trivial. In this case, I can map each bid to a point on the value function, and the problem is exactly identified. This case is discussed in Hortaçsu [22] and Kang and Puller [24].

The second case occurs when the goods are complementary, but the shocks between the goods are uncorrelated. Suppose I have two goods, a and b. In addition, suppose that the shocks to the market clearing prices of the goods are uncorrelated. This implies that the distribution of the market clearing price for b is independent of a's clearing price distribution. This independence implies that when I condition the distribution of b's market clearing price on any clearing price of a, I obtain a unique distribution. This uniqueness implies that for all bids submitted for a, the bidder expected to win an identical amount of b. This fact means that I can only identify the marginal value function of a at one value of b, thus constraining my ability to identify the multidimensional value function of the bidder. A similar condition applies for b. Together these conclusions preclude us from identifying the multidimensional value function.

The third case occurs when the goods are complementary, and the shocks between the goods are correlated. This implies that the bidder expects to win a different amount of b at each bid point for a. This is depicted in Figure 5. This heterogeneity of expectations gives the researcher a window into the multidimensional value function that is absent from the uncorrelated case. This implies that at each bid for a, the bidder expects to win a different amount of b. Hence, an additional bid point for a gives the researcher additional information about the shape of the multidimensional value function.[2]

In the bidder behavior model I allow for correlations between the market clearing prices of each good. This allows for shocks to the value of one good to be correlated with those to another good. In the absence of such correlations, the model collapses to the case of ordinary goods. Therefore, the model nests the two cases. The model can also handle negative correlations between the market clearing prices of the goods. In this case, the goods being auctioned are substitutes. Thus, the bidder behavior model I present is a general model for simultaneous uniform price auctions.

B. Estimation

I now turn to the estimation of the model. The estimation proceeds in two steps. The first step involves performing a bootstrap procedure to compute joint probability distributions of market clearing prices, $H_i(\boldsymbol{p}, \vec{\boldsymbol{y}}_i(s_i))$, which are conditional on bidder i's submitted bids. After computing these joint distributions, I turn to recovering the bidders' value functions using the derived first order conditions. Since computing the

[2] One might argue that the three cases discussed above collapse to two cases. When goods are complementary, an increase in the value of one of these goods will cause bidders to bid more aggressively for the good in a price and quantity sense. Furthermore the bidder will also bid more aggressively on the other goods being auctioned. This will tend to cause the clearing prices for all complementary goods to change in lockstep. This lockstep movement will render the second case discussed above irrelevant. When goods are complementary, the market clearing prices for these goods must be positively correlated. This conjecture provides us with a necessary condition for goods to be complements in simultaneous uniform price auctions. If the distributions of the market clearing prices are independent, then the goods being auctioned are complements. However, this test only provides us with indirect evidence concerning the existence and magnitude of complementarities between the goods.

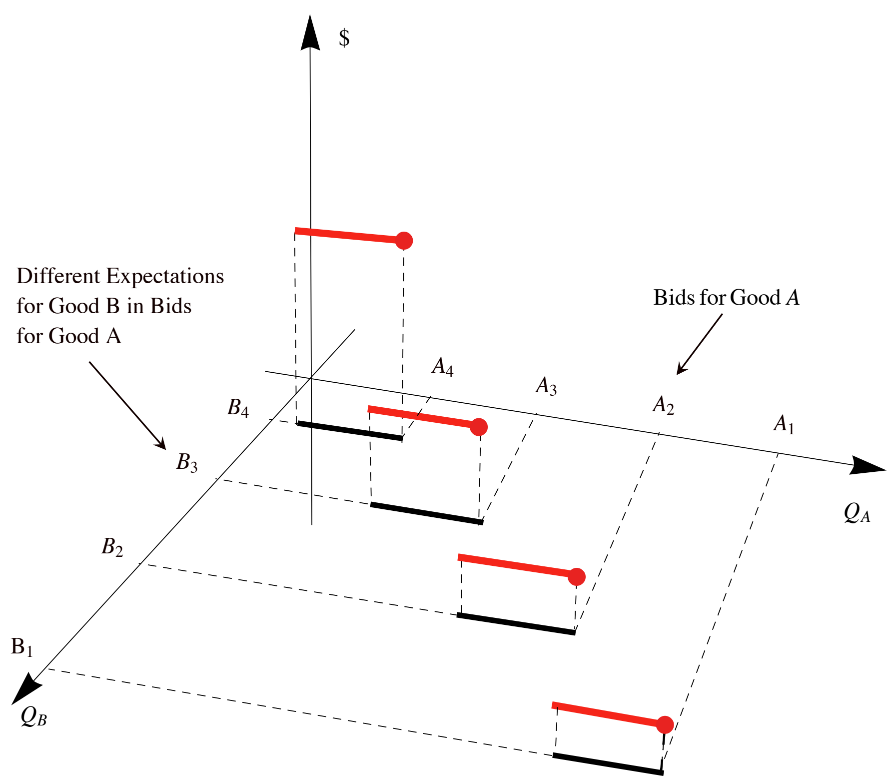


Fig. 5.: Graphical depiction of identification.

first order condition requires that I evaluate the marginal value functions at a number of points in $\mathbb{R}^M$ that far exceeds the number of bid points available to me, I make flexible parametric assumptions on the bidder value functions. After inserting the parametric value function into the first order conditions for each bidder, I perform a numerical minimization procedure to recover the parameters of the bidder value functions.

1. Resampling procedure

To estimate the joint distribution of market clearing prices, I employ a resampling procedure. This procedure was developed in a one good setting in Hortaçsu[22]. I extend the procedure to a general setting. For the succeeding resampling procedure to produce unbiased estimates, I must assume that the submitted bid points arose out of a Bayesian Nash Equilibrium. This assumption, with all the reservations that are attached, is necessary and is a standard assumption in the literature. Ideally, in order to recover this distribution, I would like to carry out the following procedure. In the theoretical bidder behavior model, I assumed that each bidder's valuation function was a function of a signal, $V(\boldsymbol{q}, s_i)$, that is drawn from a common distribution. I would like to sample signals from this distribution and construct rival bidder's value functions. I would then take the sampled rivals value functions and map them to bid points using an equilibrium bidding function. Next I would clear the market for each good and compute market clearing prices. I would perform this procedure a large number of times and collect the market clearing prices. These prices would allow me to compute the joint distribution of market clearing prices for bidder i. This procedure would be carried out for each bidder in the sample.

This ideal procedure is not available to the researcher for several reasons. First, the researcher does not have access to the bidders' signals, let alone the distribution of those signals. Second, there is not a unique equilibrium in simultaneous, uniform-price, multi-good, multi-unit auctions. This precludes me from mapping each bidder's bid points into a signal, which would allow me to estimate the distribution of the signals of the bidders. Therefore, I must develop a feasible procedure that approximates the ideal procedure in order to estimate the joint distribution of market clearing prices. In order to proceed, I assume that the observed bids arise from a Bayesian Nash Equilibrium of the above game. I use an estimator that leverages information contained in the bid points. For each bidder, I sample with replacement $N-1$ bidders from the entire set of bidders in an auction. I use the bids of the sampled bidders to construct a residual supply curve for each market, *i.e.* for each auction of each good. Next I intersect the bidder's bid curve with the residual supply curve in each market to obtain market clearing prices. I repeat this procedure a large number of times and use the resulting set of market clearing prices to compute the joint distribution of market clearing prices along with its partial distributions, conditional distributions and densities. The procedure is outlined below.

1. Fix bidder i among the total N bidders in the auction.

2. From the sample of N bidders in the data set, draw a random sample of $N-1$ bidders with replacement, giving equal probability to each bidder in the original sample.

3. For each bidder in the sample, retrieve M bid vectors, one vector for each good.

4. Construct a residual supply function for each good generated by these $N-1$ "resampled" bid vectors.

5. For each good, intersect the residual supply function with bidder i's bid vector to find the market clearing price for each good.

6. Repeat B times, where B is a large number, for each bidder and for all bidders in the data set.

This resampling procedure will output a $B \times M$ matrix of market clearing prices conditional on the bidder's bid function, where M is the number of goods being auctioned. One can use standard statistical techniques to construct the distributions which are required by the first order condition. I use $B = 5000$ for my estimation.

2. Evaluation of first order condition

In order to estimate the first order condition of the bidder behavior model, I need to make parametric assumptions on the bidder value functions. The reason for this stems from the fact that in a multi-good setting, the bidder incorporates own-good and cross-good effects into her bids. This incorporation leads to concerns about dimensionality. The first order condition in Equation 3.8 involves computing an expectation of the bidder's marginal value function. In the process of computing this expectation, the marginal value function is evaluated at each of the other goods' bid points. For example, if there are two goods, a and b, and five bids are submitted for each good, the first order condition for one bid point for good a would involve evaluating the marginal value function at each of the five bid points for good b. Since there are five bid points for good a, this requires an evaluation of the marginal value function at twenty-five different locations.[3] To compute the first order conditions for good b, the marginal value function would be evaluated at an additional twenty five points. For two goods and ten total bid points, there are fifty total unknown values. Since there are only ten bid points, I must provide a parametric restriction in order to feasibly estimate my bidder behavior model.

[3] In the discrete bidder behavior model, there is a first order condition for each bid point. Hence, for five bid points, there are five first order conditions.

This contrasts with the single good case. In the single good case, one only needs to evaluate the marginal value function at one quantity for each bid point. I will demonstrate this using the first order conditions of the bidder behavior models in the one and two good cases. In the single good case, the first order condition of the bidder behavior model is:

$$V_{y_1}(y_{1,j_1}, s_i) = p_{1,j_1} - \frac{\partial H_{p_1}(p_{1,j_1})}{\partial y_{1,j_1}} \frac{\left(\int_{y_{1,j_1+1}}^{y_{1,j_1}} V_{y_1}(q, s_i) dq - p_{1,j_1} y_{1,j_1} + p_{1,j_1+1} y_{1,j_1+1} \right)}{H_{p_1}(p_{1,j_1}) - H_{p_1}(p_{1,j_1+1})} \tag{3.7}$$

In this setting, one would estimate $H_{p_1}(\cdot)$ using the resampling procedure above. The remaining terms that need to be solved for are the value function terms. If one assumes that the marginal value function is a step function, then this equation can be solved for $V_{y_1}(y_{1,j_1}, s_i)$.[4] The result in the one good setting is a pointwise mapping of bids to valuations. Each bid point can be decomposed into a marginal valuation component and a market power, or bid shading, component. This does not emerge in the multi-good setting.

In a multi-good setting we must decompose each bid point into several components. The market power aspect remains in a multi-good setting, which follows from the uniform-price auction format. The market power in this setting is well known and has been documented by Ausubel and Cramton[3]. The other effects present in a multi-good auction setting are the cross-good effects. These cross-good effects can have a positive, negative or zero influence on the value function of the bidder depend-

[4]Depending on the type of step function the marginal value function takes, a different solution method is employed. If one is estimating the upper bound of the marginal value function, then the integral of the marginal value function would become $V_{y_1}(y_{1,j_1}, s_i)(y_{1,j_1} - y_{1,j_1+1})$. If one is estimating the lower bound of the marginal value function, then the integral of the marginal value function would become $V_{y_1}(y_{1,j_1-1}, s_i)(y_{1,j_1} - y_{1,j_1+1})$, in which case a system of equations would arise.

ing on the types of goods being auctioned. These cross-good effects are present even in a situation where there is competitive bidding.

I impose a parametric functional form on each bidder's value function. I use flexible functional forms that do not impose burdensome dimensionality requirements. In addition, I use functional forms that require the own good marginal valuation, "demand," functions to be monotonically decreasing. This arises from the intuition of diminishing marginal returns. This does not preclude the cross-derivatives from being non-zero. In summary, I make the following restrictions on the assumed bidder value functions.

Assumption 3 (Parametric Value Function Assumptions) *I will assume the following about the parametric value functions:*

1. *Bidder i's parametric value function is twice differentiable.*
2. *Bidder i's parametric value function is strictly increasing in* $\boldsymbol{q}$. *Therefore,* $\forall\, \boldsymbol{q}^A, \boldsymbol{q}^B \in Q^M : q_i^A > q_i^B$ *for some* $i \in \{1, \ldots, M\}$, *then* $V(q^A) > V(q^B)$.
3. $V(\mathbf{0}) = 0$.
4. $\frac{\partial V(\boldsymbol{q})}{\partial q_i} \leq 0 \,\forall\, i \in \{1, \ldots, M\}$
5. $\frac{\partial^2 V(\boldsymbol{q})}{\partial q_i q_j} \geq 0 \,\forall\, i, j \in \{1, \ldots, M\} \,|\, i \neq j,$

There are many functional forms which fit these assumptions. I chose a functional form which is both consistent with these assumptions and familiar to economists. I assume that the bidder value functions take a Cobb-Douglas form.

$$V(a, b, c) = \eta a^{\alpha} b^{\beta} c^{\gamma}$$

I make the following assumptions on this functional form:[5]

$$\{0 \leq \alpha < 1,\ 0 \leq \beta < 1,\ 0 \leq \gamma < 1,\ \alpha + \beta + \gamma \leq 1\}$$

After making functional form assumptions for the bidder valuation functions, I substitute these into the first order condition of the bidder behavior model. I now have a first order condition that is feasibly estimated. I denote the assumed functional form of the bidder value function as $\hat{V}(\boldsymbol{q})$. I denote the estimator for the joint distribution of the market clearing prices as $H^{\boldsymbol{R}}(\cdot)$.

[5] I make the assumption that $\alpha + \beta + \gamma \leq 1$ in the Cobb-Douglas formulation to rule out cases of increasing returns to scale. Economists will be familiar with this assumption in a growth model or production function model context. I prohibit increasing scale economies here. If they were allowed, a bidder would value a package of goods with double the quantity of each good, more than twice as much as the original package. Since bidders are risk-neutral and the goods being auctioned are similar to insurance, this potential more than doubling of valuation would be inconsistent. There is one additional, technical reason. When performing the counterfactual direct revelation mechanism, bidders who exhibit increasing returns to scale will necessarily be allocated virtually all the goods being auctioned. The non-negative assumptions are purely technical in nature.

$$\sum_{j_2=1}^{J^2+1}\Big(\big[H^{\boldsymbol{R}}(p_{1,j_1},p_{2,j_2})-H^{\boldsymbol{R}}(p_{1,j_1-1},p_{2,j_2})\big]-$$
$$\big[H^{\boldsymbol{R}}(p_{1,j_1},p_{2,j_2-1})-H^{\boldsymbol{R}}(p_{1,j_1-1},p_{2,j_2-1})\big]\Big)\hat{V}_{y_1}(y_{1,j_1},y2,j_2,s_i)+$$
$$\sum_{j_2=1}^{J^2}\big(H^{\boldsymbol{R}}(p_{1,j_1},p_{2,j_2})-H^{\boldsymbol{R}}(p_{1,j_1-1},p_{2,j_2})\big)\int_{y_{2,j_2+1}}^{y_{2,j_2}}\hat{V}_{y_2y_1}(y_{1,j_1},q)dq=$$

$$\big(H^{\boldsymbol{R}}_{p_1}(p_{1,j_1})-H^{\boldsymbol{R}}_{p_1}(p_{1,j_1-1})\big)p_{1,j_1}-$$
$$\left(\begin{array}{l}\dfrac{\partial H^{\boldsymbol{R}}_{p_1}(p_{1,j_1})}{\partial y_{1,j_1}}\left(\left[\displaystyle\sum_{j_2=1}^{J^2+1}\big(H^{\boldsymbol{R}}(p_{2,j_2}|p_{1,j_1})-H^{\boldsymbol{R}}(p_{2,j_2-1}|p_{1,j_1})\big)\int_{y_{1,j_1+1}}^{y_{1,j_1}}\hat{V}_{y_1}(q,y_{2,j_2})dq\right]\right.\\ \qquad\qquad\left.-\,p_{1,j_1}y_{1,j_1}+p_{1,j_1+1}y_{1,j_1+1}\right)+\\ \displaystyle\sum_{j_2=1}^{J^2+1}H^{\boldsymbol{R}}_{p_1}(p_{1,j_1})\left(\frac{H^{\boldsymbol{R}}(p_{2,j_2}|p_{1,j_1})}{\partial y_{1,j_1}}-\frac{H^{\boldsymbol{R}}(p_{2,j_2-1}|p_{1,j_1})}{\partial y_{1,j_1}}\right)\int_{y_{1,j_1+1}}^{y_{1,j_1}}\hat{V}_{y_1}(q,y_{2,j_2})dq+\\ \displaystyle\sum_{j_2=1}^{J^2}H^{\boldsymbol{R}}_{p_2}(p_{2,j_2})\frac{H^{\boldsymbol{R}}(p_{1,j_1}|p_{2,j_2})}{\partial y_{1,j_1}}\int_{y_{2,j_2+1}}^{y_{2,j_2}}\big(\hat{V}_{y_2}(y_{1,j_1},q)-\hat{V}_{y_2}(y_{1,j_1+1},q)\big)dq\end{array}\right) \tag{3.8}$$

3. Recovering the parameters

The next step in the estimation procedure is to recover the parameter values for the assumed functional forms. This part of the procedure is independent of the particular functional form being used and is similar to nonlinear least squares. Bidder i submits a total of $J=\sum J^i$ bids in M markets. Therefore, there are J restrictions with which to estimate the value function parameters. As long as J is at least as large as the number of value function parameters, I have enough information to estimate each parameter. Assuming this qualification is met, I then equate each first order condition with zero by rearranging the terms of the equation. Once this is complete, I square each first order condition. To construct an objective function, I sum these squared first order conditions. I then use numerical minimization techniques to find the value function parameters that best fit the first order conditions constraining the parameters by the assumptions which are specified above.

4. Computing efficiency

After computing the parameters of each bidder's value function, I now proceed to the final steps of the estimation procedure, computing the degree of efficiency achieved by the auction and estimating its significance. The estimated parameters allow me to construct a value function for each bidder that maps any package of goods to a value. The package of goods is a triple in $\mathbb{N}^3$. The value function fully takes into account the interdependent valuation structure of each bidder. This mapping from packages to value provides me with the ability to run a counterfactual auction in which the allocation of the set of available goods maximizes social value. To run this counterfactual auction, I assume that each bidder submits her value function to the auctioneer. The auctioneer proceeds to allocate the set of goods such that the social value is maximized. This is performed by constructing a (utilitarian) societal value function which is equal to the sum of all bidder's value functions. Equal weight is put on each bidder's value function. This societal value function is maximized subject to the constraint that the number of unit-goods allocated cannot exceed the number of unit-goods available. The allocation is computed using numerical maximization techniques.

The result of this exercise will output the societal value of the first best auction allocation. However, the *level* of this value is not our goal. The *ratio* of the first best value to the actual value is instructive, for it provides a measure of the degree to which the actual auction mechanism achieves its stated goal of maximizing the social value of the auction. To compute the value of the actual auction mechanism, I map the actual allocation to social value using the same societal value function employed in calculating the social value of the first best outcome. Finally, I compute the degree of efficiency achieved by dividing the social value of the actual auction allocation by the social value of the first best auction allocation. This is my main statistic of interest.

In order to ensure that my statistic of interest contains sufficient information, I construct a measure of the estimation error inherent in the proceeding estimation procedure. Ideally, I would derive the distribution of my test statistic, construct an acceptable level of variation, and compare it to my point estimate. This would involve deriving a distribution from the sources of error in my estimation procedure. Given that I do not possess any *a priori* theoretical restrictions that provide guidance for such an exercise, I must proceed via an alternate tact. Due to the complexity of this problem, I will employ the "jackknife-after-bootstrap" proposed by Efron [11] and Efron and Tibshirani [12] to compute the standard errors of my point estimate of the efficiency achieved by the auction.

Let the efficiency of the auction be defined as $\Gamma \in \mathbb{R}$. By construction $\Gamma \in [0,1]$. The estimate of Γ is $\hat{\Gamma}_B(y_i^m)$, a function of each bidder's demand curve. $\hat{\Gamma}_B$ is computed by performing B bootstrap simulations for each bidder to compute the value function parameters. The formula for the "jackknife-after-bootstrap" is:

$$v\hat{a}r(\hat{\Gamma}_B(y_i^m)) = \frac{N}{N-1}\sum_{j=1}^{N}\left(\hat{\Gamma}_{B(j)}(y_i^m) - \left(\frac{1}{N}\sum_{i=1}^{N}\hat{\Gamma}_{B(j)}(y_i^m)\right)\right)^2 \tag{3.9}$$

The estimate of $\hat{\Gamma}_{B(j)}(y_i^m)$ is performed by excluding, across all bidders, all re-samples that include y_i, computing the value function parameters for each bidder, and performing the counterfactual first-best auction. The procedure is repeated N

times. The N values of efficiency are used to construct bounds on the point estimate of the efficiency ratio.

The rationale for using the procedure in this manner arises from the sources of estimation error. The error in this estimation procedure follows from the fact that the researcher is not in possession of two pieces of information. First, the researcher does not possess the signal distribution used by the bidders to construct expectations of market clearing prices. Second, the researcher does not possess an equilibrium bidding strategy that corresponds to the specific equilibrium strategy played by the bidders in the auction. Lacking these two pieces of information, the researcher is left with producing an estimate of bidders' expectations of market clearing prices. The error of this estimation enters via each bidder. Thus the reason for excluding each bidder's demand function in turn to compute the "jackknife-after-bootstrap."

CHAPTER IV

INSTITUTIONAL SETTING OF AUCTIONS

This chapter will lay out the institutional setting of the financial transmission rights auctions in Texas. Electricity firms purchase financial transmission rights to hedge against price uncertainties they face in transporting power across the electricity grid. They were proposed by Hogan[21]. Often times, they face these uncertainties when entering into a long-term contract to provide power. Some firms purchase these financial rights as a purely speculative instrument, since they provide returns which are unlikely to be correlated with other standard financial assets. In this way, financial transmission rights are similar to forest timber rights that large university endowment funds purchased beginning in the 1980's. Financial transmission rights are sold at auctions in a similar fashion to US treasury bonds. However, the nature of financial transmission rights and the benefits that they provide lead firms to value a package of different types of these rights higher than the sum of the individual components. To further illustrate the uses for financial transmission rights, I will construct illustrative examples.

The economics of electricity production and transmission lead suppliers to locate generating facilities away from points of consumption. This setup necessarily involves the transmission of electricity over a network of transmission lines. For purposes of this discussion, the pertinent facts are that electricity must be transported from generation facilities to consumers and this transportation can be costly. To illustrate these costs, let us consider the following example. There is an electricity grid with two locations and two links that connect them. The links are of equal length. This setup is depicted in Figure 6.

A low cost supplier is located at point A, and it has a constant marginal cost

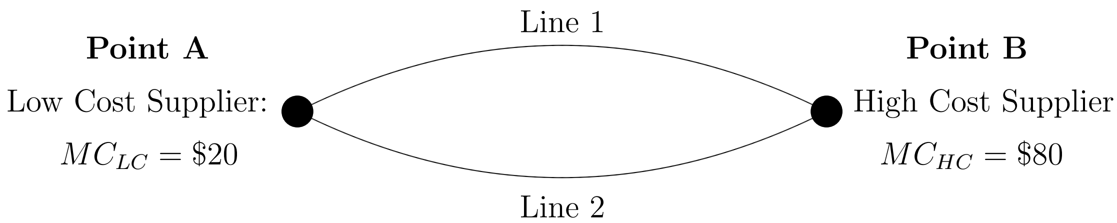


Fig. 6.: Sample grid configuration.

of \$20 per unit of electricity. A high cost supplier is located at point B, and it has a constant marginal cost of \$80 per unit of electricity. In addition to the high cost supplier, there is a consumer located at point B. This customer has a long term contract with the low cost supplier to supply it power for \$40 per unit of electricity. In the case when the transportation of the power pursuant to this long term contract is costless, the low cost supplier provides all the power to the customer for \$40 per unit of electricity. By the laws that govern electricity flow, half of this power will be transported over line one, and the other half will be transported over line two.

Suppose that the ability of line one to transmit power is diminished by one half. Since half of the power is transported over this line, one fourth of the contract cannot be met by the low cost supplier. In this case, the low cost supplier is forced to purchase power from the high cost supplier for \$80 per unit of electricity to fulfill its contract obligations. If this increase in the cost of providing power occurs enough, the low cost supplier will no longer find it advantageous to enter into such a contract. Above some threshold and assuming high transaction costs of developing a state-contingent contract, the low cost supplier will only find it profitable to enter into a contract to serve three quarters of the customer's demand for \$40 per unit of electricity. In this case, the residual demand would be met by the high cost supplier for \$80 per unit of electricity. This results in inefficiency. This is due to less power being supplied by the low cost supplier.

An alternate outcome can occur in the case when the low cost generator can purchase a hedge against such price increases. Suppose the low cost generator can purchase financial transmission rights that pay it the difference between its costs and those of the high cost generator.[1] In this case, the low cost generator can enter into a contract to supply all of the customer's demand for $40 per unit of electricity plus the cost of financial transmission rights. This outcome increases the efficiency of the resulting transactions, since more of the power would be supplied at the least cost price, and the lines connecting A and B would be fully utilized.

This example has offered an impetus for firms to purchase financial transmission rights and demonstrated how these rights can increase efficiency. What this example has not shown is how a firm might value a package of these rights more than the sum of the values of its individual components. I will present two examples that show this.

The first is an extension of the previously developed example. To show complementarities between these rights, consider the following complication. The ability of both line one and line two to transport power can be diminished by one half. The low cost supplier currently owns financial rights for lines one only. In addition, there are two potential customers located at B, a low value, small customer and a high value, large customer. The low value customer is willing to purchase power for $40 per unit of electricity. The high value customer is willing to purchase twice as much power for $50 per unit of electricity. If transportation costs are high enough, the low cost supplier only finds it profitable to enter into a contract with the low value customer without financial rights on both lines. In this state, the low cost supplier

[1] A financial transmission right returns the price difference between two locations on the electricity grid. In this example, the prices for electricity at points A and B equal the marginal costs of the low and high cost suppliers, respectively.

and low value customer enter into a contract, and the high cost supplier and high value customer enter into a contract. In this outcome, the full capacity of the lines connecting A and B is not utilized.

In this example, the low cost supplier would value the package of financial rights for lines one and two greater than the sum of their individual values. This arises because holding only one financial right enables the supplier to profitably enter into a contract with the low value customer. If the low cost supplier held both financial rights, then it would find it profitable to enter into a contract with the high value customer. Since owning an additional financial right enables the low cost supplier to capitalize on this opportunity that creates more than twice as much value, it values the package of financial rights greater than the sum of the individual values.

Another reason a firm values a package of financial transmission rights more than the sum of its parts is due to the way power flows on a transmission network, which was alluded to above. On a complicated transmission network, power follows the path of least resistance. If two parties enter into a contract for the delivery of power from one party to the other, the fulfillment of that contract does not physically cause power to flow directly from the sending to receiving party. The power is simply produced by one party and flows in all directions across the grid in proportion to the "resistance" it encounters. If there is a transportation cost incurred by the sending party, then it must assemble a package of financial rights that resembles the manner in which its power would travel to the receiving party. Since the ability to hedge against such costs is what facilitates the formation of value enhancing contracts, a package of financial transmission rights can be worth more to a counter-party than the sum of the individual values.

I am studying auctions for financial transmission rights that occurred in the Texas electricity market over the course of 2002. There were three different types of financial transmission rights in the auction that I analyze. Each type returned "price differences" between different locations on the electricity grid. These rights were sold in simultaneous uniform price auctions. There was one auction per type of financial transmission right. I will briefly describe the Texas electricity market. Next, I will specify the institutional details of the auctions in which these rights were allocated to firms. Finally I will describe the bidders that participated in this market.

A. Details of the Texas electricity market

During 2002 the electricity market in Texas was divided into a handful of large, contiguous zones which were used to aid in the market dispatch of electricity supply. Generation facilities and demand were placed into these zones according to how they affected the transmission network. Places with similar effects were placed in the same zone. There are groups of major transmission lines that connect these zones, similar to interstate highways connecting states, which are monitored continuously. When the flow of electricity is within the capacity of the transmission lines, there is one market for power. When the flow of electricity on these major transmission lines begins to approach acceptable limits, there is one market per zone, and the impact of producing power in these zones on the flow of power over these major transmission lines is considered. This separation into zones creates different prices for power in each zone. These differences in prices are the source of the risk that counter-parties take when entering into a contract with a party that is located in a different zone. There were four zones in 2002, the North, Houston, South and West zones. There was a price of transmission established on three transmission corridors: the corridor that connected the South and Houston zones, the South and North zones and the West and North zones. These transmission prices were related to the price differences among the zones that occurred when the power flow in any of these transmission corridors reached acceptable limits.

To illustrate how a firm considered transportation costs in this market, I will compute the package of rights that a firm would need to have assembled to hedge transportation costs that would have stemmed from a contract to supply power from the South zone to the North zone in 2002. According to the model of the Texas electrical grid, one unit of power produced in the South zone to be delivered in the North zone would traverse the transmission network in the following manner: 4.3% would flow across the transmission corridor that connects the West zone to the North zone, 39.2% would flow across the transmission corridor that connects the South zone to the North zone, and 18.5% would flow across the transmission corridor that connects the South zone to the Houston zone.[2] In order to hedge against paying transportation costs when these transmission corridors were constrained, the supplier would need to have purchased a portfolio of financial transmission rights resembling the previous percentages.

B. Details of financial transmission right auctions

Financial transmission rights in Texas are sold in auctions that take place annually and monthly. Rights sold in the annual auction pay the holder the transmission price of a transmission corridor for an entire year. Rights sold in the monthly auctions pay the holder the transmission price of a transmission corridor for one month. Because these are share auctions, bidders can submit multiple bid points in the auction. There is one uniform price auction per Financial Transmission Right, and they are run simultaneously. Bidders submit price-quantity pairs for each auction. In 2002

[2] These numbers were derived from the zonal average weighted shift factors that ERCOT used for the annual Transmission Congestion Rights auction for 2002.

bidders were not able to submit package or combinatoric bids. The number of rights available for each transmission corridor is common knowledge and is *ex ante* available. For the annual auction, the number of rights available for each transmission corridor is a function of the capacity of the transmission corridors. Forty percent of these determined capacities are available in the annual auction. For monthly auctions, the capacity of each transmission corridor is recomputed using the most recent information for the month over which the rights are in effect. For each transmission corridor, the number of rights distributed in the annual auction is subtracted from the newly calculated monthly capacity number. Hence, a residual amount of rights is offered in the monthly auctions. Annual auctions occur before December fifteenth of the year preceding the year in which the annual rights will be in effect. Monthly auctions occur before the fifteenth day of the month preceding the month in which the monthly rights will be in effect.

There is an ownership limit for these rights in the auctions. Market guidelines impose a maximum share of twenty-five percent of the total rights per transmission corridor. This constraint is imposed at the time of market clearing in each auction as well as on secondary market trades that are registered with the grid operator. It is conceivable that market participants can establish a contract that would mimic a secondary market trade and not report this contract. Using such a contract, a market participant could establish a de facto share of rights which exceeds the twenty-five percent ownership limit.

One Financial Transmission Right is in effect for all hours during the period that the right is in effect. In terms of modeling bidder behavior, I will assume that there is no secondary market for these rights. Relaxing this assumption would increase the complexity of the bidder behavior model considerably, without offering any additional benefit to capturing the effects that complementarities have on bidder behavior. See

Haile [18] for a bidder behavior model where resale is allowed.

A secondary market further underscores the need to examine the efficiency of the auction allocation in this setting. A vibrant secondary market for financial transmission rights in Texas did not exist in 2002. There was a market institution for firms to trade any financial rights they owned, but it was not utilized. Furthermore, the structure of the rights was such that it would be difficult for secondary market transactions to occur. Financial transmission rights return a stream of revenue related to price differences on the electricity grid. The period that these rights were in effect was continuous from start to end date. This period was either a month or a year, depending on the type of right. Therefore, in order for a secondary market transaction to take place, a firm owning a financial transmission right would need to no longer have an interest in using the stream of revenue to hedge against electricity price differences, while another firm would need to develop a need for this capability. This boolean change in interests is likely not to occur outside of a simultaneous entry by one firm and exit by another. In fact, the Texas electricity market witnessed growth in the number of firms over this period, which further underscores the low probability of such an event. These two facts offer suggestive evidence that there was no significant secondary market for financial transmission rights in Texas in 2002.

If there is no significant secondary market, the initial allocation of financial transmission rights determines the level of efficiency that will be achieved. This provides further justification to assess the efficiency of the initial allocation.

C. Bidder summary data

I analyze the annual financial transmission right auction that took place in 2002. The annual rights for 2002 covered the period from March 1 to December 31. The annual auction was held on January 15, 2002. There were twenty-two bidders in the annual auction. There was vigorous competition for the rights that were offered. For every right that was offered, the average quantity demanded was 4.4. The total auction revenues were $70 million. The average number of bid points submitted per bidder was 32, the median was 14.

There was a diverse group of bidders in these auctions. The set of bidders included investor owned utilities, merchant generators, power purchasers and financial firms. Investor owned utilities own generation facilities and serve demand. Merchant generators own generation facilities. Power purchasers only demand electricity. In addition, the set of bidders included city owned utilities, small electric cooperatives, and power trading companies.

The rights awarded in the annual auction were concentrated among a few, large bidders. In the annual auction the top five bidders won eighty-four percent of the rights that were auctioned. In the monthly auctions, the percentage of rights awarded to the top five bidders varied from sixty-six percent to ninety-five percent and averaged seventy-five percent. Since the average number of bidders in these auctions was eighteen, this means that for the average monthly auction about twenty-eight percent of the bidders won seventy-five percent of the rights that were available. In terms of auction value, the top two bidders in terms of the amount paid for these rights were responsible for forty-six percent of the auction revenues. The top five bidders were responsible for seventy-four percent of auction revenues.

CHAPTER V

RESULTS

I now discuss the empirical results which follow from the application of the empirical bidder behavior model to the auction bid data. I discuss the results in three parts. First I offer evidence that the distributions of market clearing prices are not independent, thereby satisfying a necessary condition for complementary goods. Next I present the bidding behavior of two large bidders in the annual auction whose behavior drastically differs. This difference in behavior is driven by the the difference in the magnitude of complementarities in each bidder's necessary conditions. Next I present the efficiency properties of the realized allocation in the annual auction with respect to the socially optimal allocation. In order to compute the socially optimal allocation, I conducted a counterfactual auction in which each bidder reveals her value function to the auctioneer. I find that the efficiency of the simultaneous uniform price auctions in this setting is low.

A. Market outcomes and resampling procedure

Before turning to the results of individual bidders, I present the market outcomes for the annual auction. There was vigorous competition for the South to Houston, South to North and West to North financial transmission rights. In each market there were at least four bids for every right available. The most competition for rights was for South to North financial transmission rights. This is likely due to the fact that this transmission corridor was expected to be the most congested, and thus a higher expected return would result. The South to North market cleared at the highest price. Since these auctions were simultaneous uniform price auctions, all bids above the market clearing price paid the clearing price to the auctioneer. The auction revenue for each market is denoted in figures 7, 8, and 9 as gray rectangles.

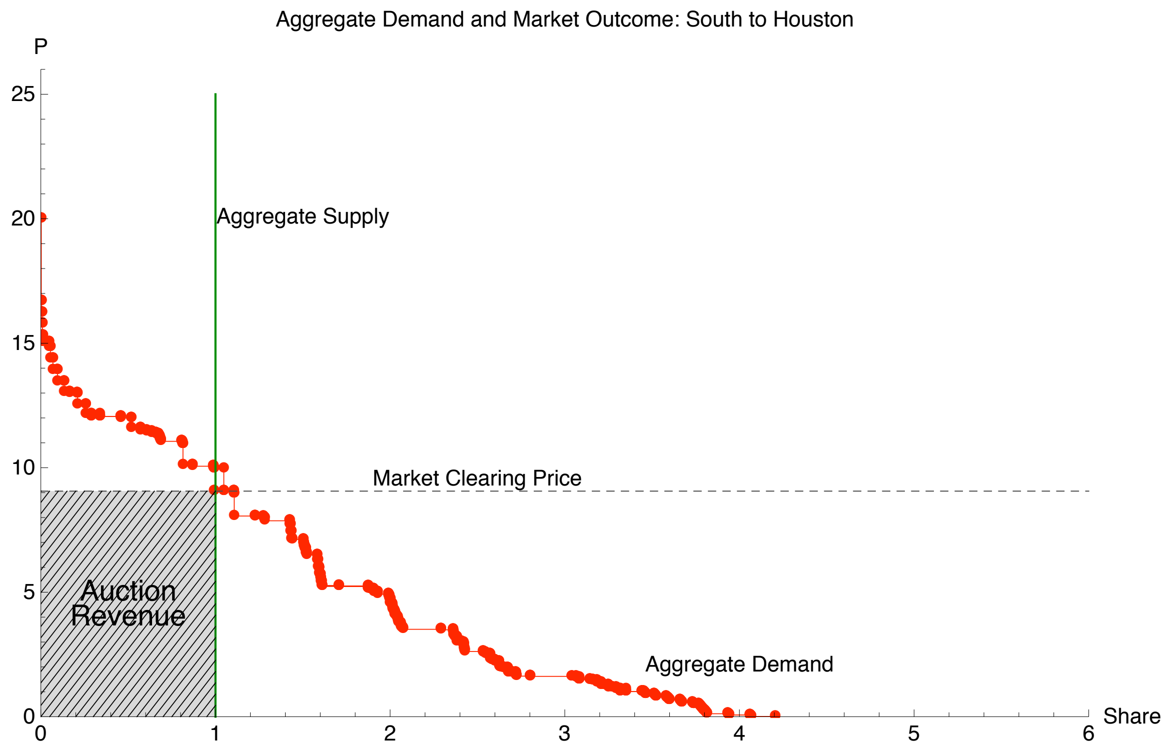


Fig. 7.: South to houston market outcome for the annual auction.

As discussed previously, I employed a resampling procedure to estimate an expectation of market clearing prices for each bidder. This procedure involves resampling from the set of bidders to create a set of residual supply functions. This set is then used to compute market clearing prices, which are in turn used to compute probabilities related to this distribution. In figure 10 we can see thirty residual supply curves constructed during this process for the bidder Morgan Stanley. The slopes of these residual supply curves, by casual inspection, lie within a small range. Thus each residual supply curve can be thought of as a parallel shift of an underlying curve. This result is consistent with a setting of private information in which the bidders are

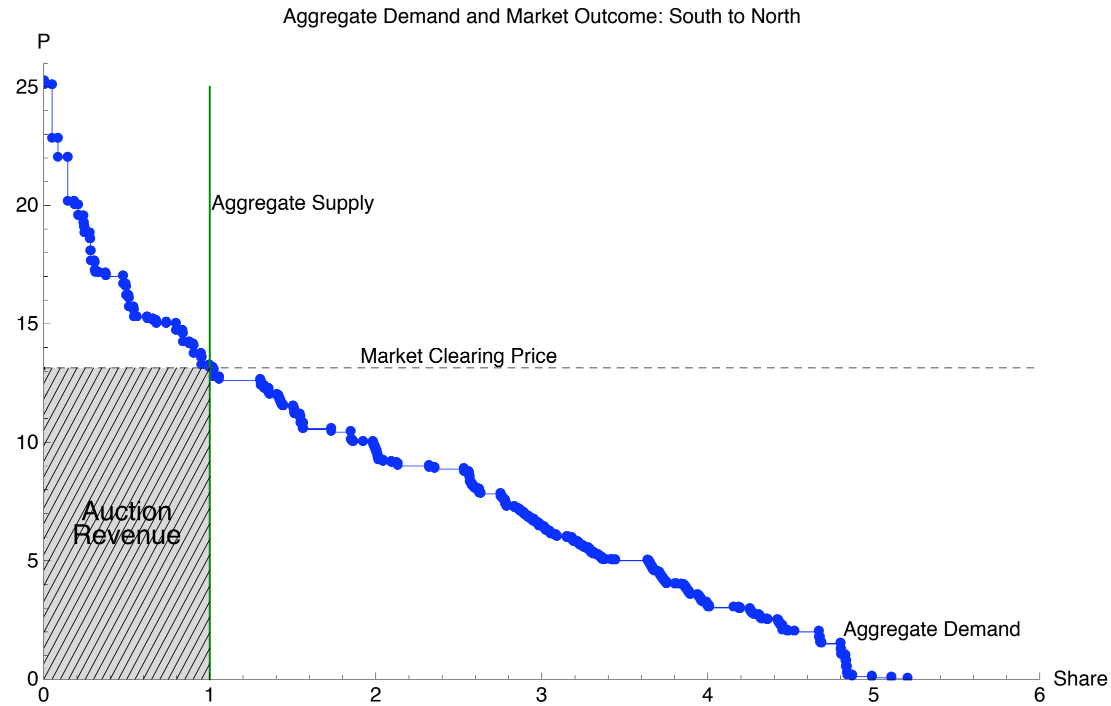


Fig. 8.: South to north market outcome for the annual auction.

symmetric, and the bidders valuations vary because they receive unique signals. Since I assume that the set of bidders is deterministic, the uncertainty lies in the *set* of signals drawn by the bidders. This is expected, since bidders' value of a given portfolio of financial transmission rights depends upon their private contract positions in related electricity markets. While these positions do not completely determine bidders' signals, they are likely to comprise a large portion.

It is here that we see the logic behind the resampling procedure. Given that the researcher does not have access to the signal distribution, nor the actual draws from it, an alternative is to use the information contained in the bid curves submitted by each bidder. Since the signal draws are contained within each bidder's bid curves, I can use these curves as a source of information about the signal draws. Combining

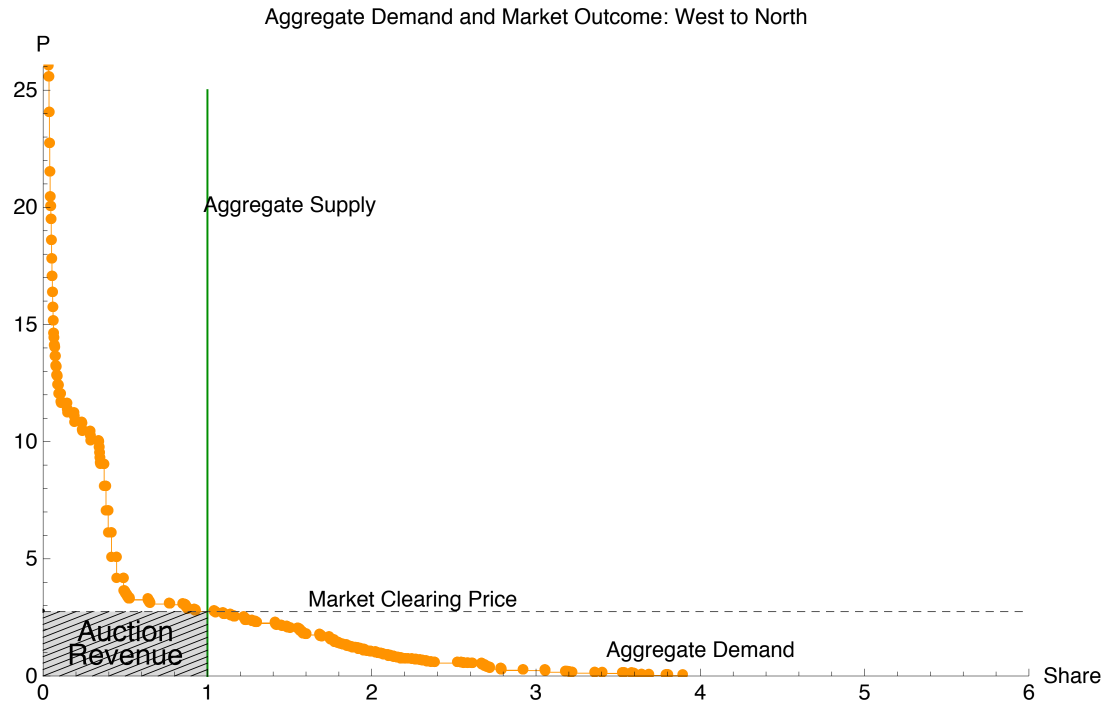


Fig. 9.: West to north market outcome for the annual auction.

this insight with a bootstrap routine allows the researcher to estimate possible signal draws via random sampling from the set of bid vectors. This process is repeated, thereby creating, effectively, an estimate of the *joint* distribution of signals. It is in figure 10 that we see this insight put into practice.

B. Joint distribution of market clearing prices

I now turn to a discussion of the properties of the joint distribution of market clearing prices which are computed as part of a resampling procedure. To determine an optimal bidding strategy, a bidder must form expectations concerning the distribution of the clearing prices in each uniform price auction. Since the researcher does not have access to the signal distribution of bidders, nor an equilibrium bidding strategy

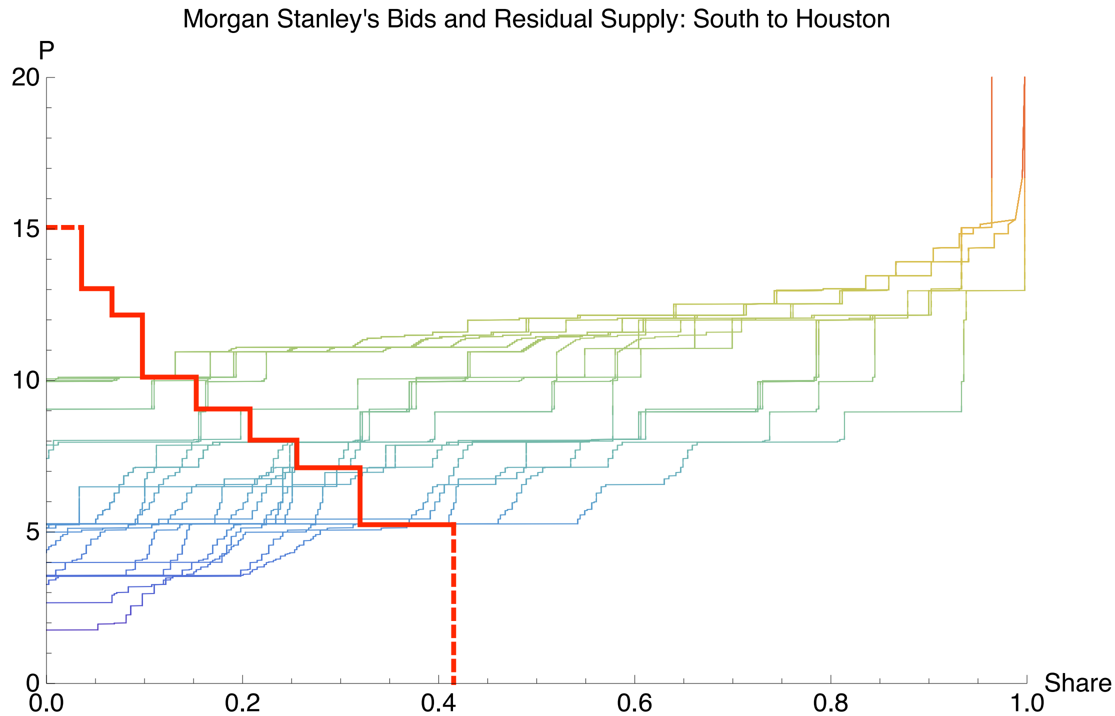


Fig. 10.: Morgan Stanley's bid function and a sample of thirty residual supply curves used to compute a distribution of market clearing prices.

in this auction, information contained in the set of bids submitted in the auction is "bootstrapped" in order to construct an estimate of the distribution of market clearing prices. I postulated previously that when goods are complements, the distributions of their market clearing prices should be positively correlated and dependent. I will now present evidence that this is indeed the case.

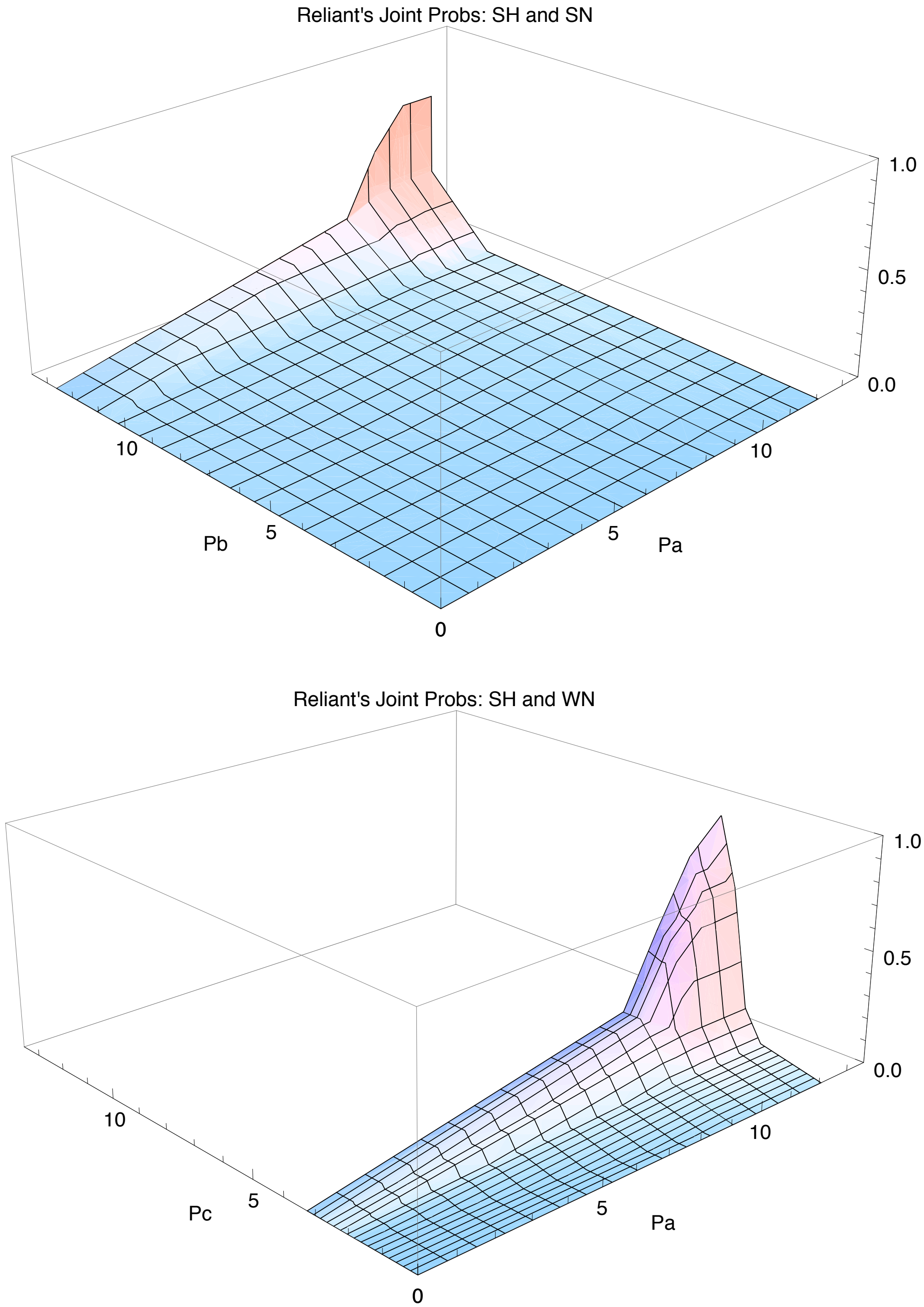


Fig. 11.: Two of Reliant's joint distributions of market clearing prices.

I will focus on the distributions of Reliant's market clearing prices. Reliant submitted a relatively small number of bid points which lends its distributions to display. In addition, these distributions are representative of other bidders. I performed five thousand resamples. The resampled market clearing prices are highly correlated. Table I shows the correlation between these resampled market clearing prices. This is evidence that the distributions between these prices are not independent. A graphical depiction of the joint empirical distributions between these markets appears in Figure 11. One can ascertain from the shapes of these distributions that the joint distribution between the prices of South to Houston and South to North prices are not independent.

Table I.

Correlation between the resampled market clearing prices of Reliant in the annual auction.

	SH	SN	WN
SH	1		
SN	0.848	1	
WN	0.799	0.761	1

Further evidence of the dependence appears in Figure 12. Here I show the empirical distribution function of the South to Houston clearing prices along with the conditional distributions for the South to Houston prices. The conditional distributions show the probability that the market clearing price in South to Houston is less than or equal to a given South to Houston bid price conditional on the clearing price in South to North being less than a particular bid price in the South to North auction.

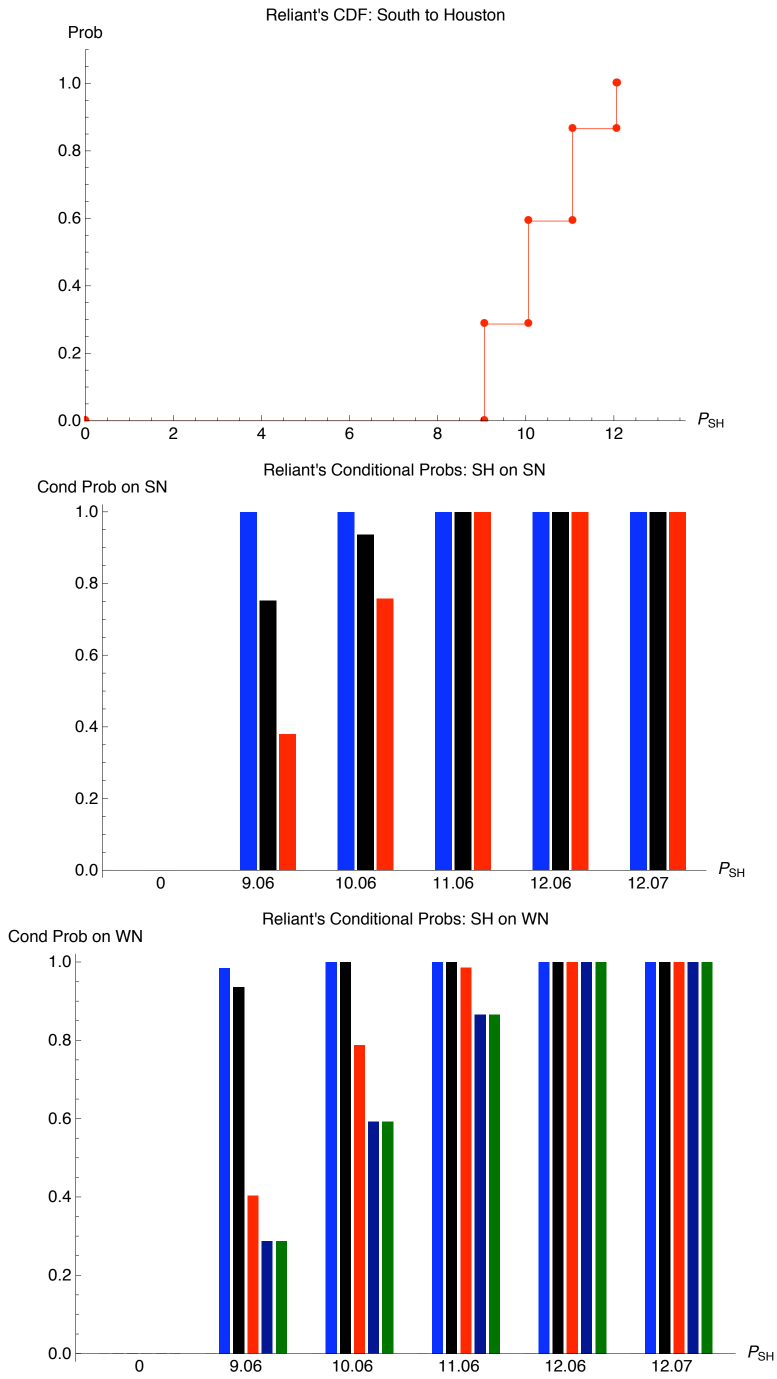


Fig. 12.: Reliant's distribution of market clearing prices: south to Houston.

Each bar in the middle chart represents a pair of a South to Houston bid price and a South to North bid price. If the heights of the bars did not change for a fixed bid price in South to Houston, then these distributions would be independent. Since these bars do change in height as we change the bid price for South to North, this is further evidence that these distributions are dependent. In addition, as the South to North conditional bid price increases, the probability that the market clearing price in South to Houston is less than a given South to Houston bid price decreases. This is consistent with complementary goods, since receiving a high value signal for South to North is correlated with receiving a high value signal for South to Houston. This logic is consistent with the conditional distribution for South to Houston and West to North.

Market power plays a role in the bidder behavior in uniform price auctions since bidders have an incentive to shade their bids, or reduce demand. In the bidder behavior model this incentive is reflected in the partial derivative of the distribution of market clearing price with respect to bid quantity. If by increasing the quantity bid at a particular price changes the probability that the market clearing price is less than that bid price, then the bidder possesses market power. Since increasing the quantity bid shifts the market demand curve to the right, so that more of the curve is at a higher price, the probability that the clearing price is less than the price at which the quantity was increased decreases. I refer to this form of market power as own good market power, since the effect pertains to changes in the probability distribution in the market in which the quantity was changed. There are two forms of this own good market power in the bidder behavior model, an unconditional and a conditional form:

$$\frac{\partial H_{p_1}^{\boldsymbol{R}}(p_{1,j_1})}{\partial y_{1,j_1}} \qquad \frac{\partial H^{\boldsymbol{R}}(p_{1,j_1}|p_{2,j_2})}{\partial y_{1,j_1}} \tag{5.1}$$

Since we are in a multi-good setting in which the goods are complements, there are several forms of market power. In addition to own good market power, there is cross good market power. It is the effect that changing a bid quantity in one market has on the probability distributions in other markets. The cross good market power term in a two good setting is:

$$\frac{\partial H^{\boldsymbol{R}}(p_{2,j_2}|p_{1,j_1})}{\partial y_{1,j_1}} \tag{5.2}$$

These cross market effects are present, because changing the quantity bid at a particular price in one market affects the *joint distribution* of market clearing prices. Mechanically what occurs when a bid quantity is increased is a reduction in the set of events in which the clearing prices in the affected market are below the price at which the quantity was changed. Since the market prices are positively correlated, this tends to reduce the number of events in which all prices are low. Thus, the entire distributions shifts so that lower price outcomes are less likely. Intuitively, these effects arise from the fact that the goods being sold in these auctions are complements, resulting in correlated "shocks to values." For example, if the expected value of the South to North instrument increases, the values of the South to Houston and West to North instruments are also likely to increase. Hence, an increase in demand in one market leads to an increase in demand in the other markets.

Figure 13 depicts Reliant's own good market power terms in the South to Houston market in the annual auction. The unconditional own good market power is in the left panel. There is positive market power over the support of Reliant's bid prices, although the absolute magnitude is small. The conditional own good market power for the South to North and West to North markets is qualitatively similar. Note that by fixing a South to Houston bid price and varying the South to North, or West to North, price increases this market power.

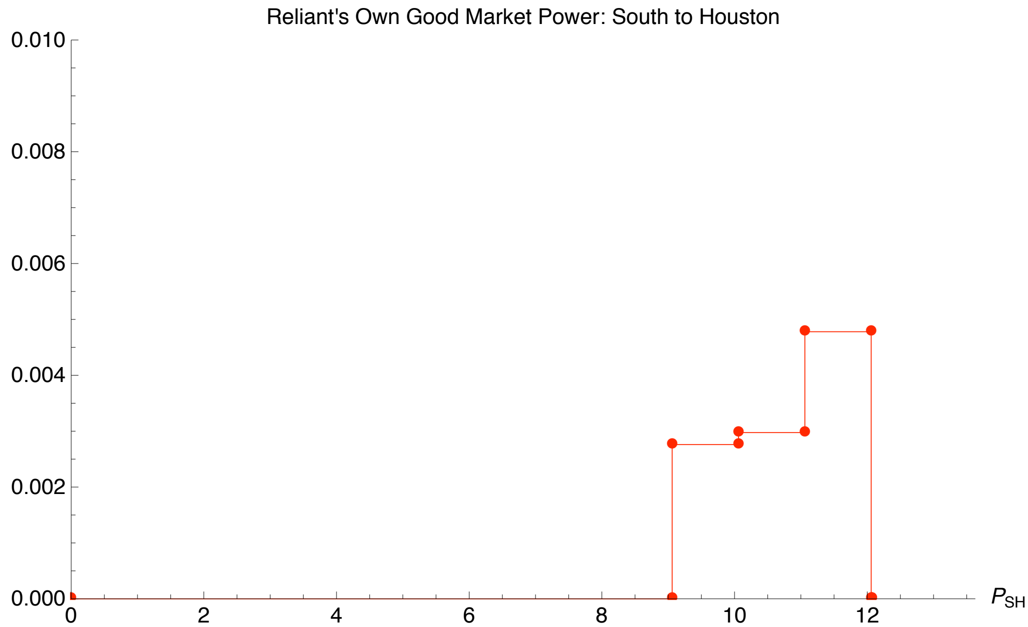


Fig. 13.: Reliant's market power: south to Houston.

C. A tale of market power and "going for it"

I now turn to the description of two bidders' behavior which provide a window into how complementarities can affect bidding behavior. There are two countervailing forces that drive bidders to submit bids that differ from their valuations in this auction format: market power and complementarities. While increasing market power causes a bidder to *reduce* demand, increasing complementarities causes a bidder to *increase* demand. In the parlance of Kagel and Levin[23], the latter effect is referred to as the "synergy effect." One advantage of the bidder behavior model that I estimate is that these effects can be measured and compared. The synergy effect for some bidders is large enough to cause bidders to submit bids which exceed their realized own good valuations. For other bidders the market power force outweighs their synergy effects. I will present the estimated value functions of two bidders at these extremes. Both are large bidders in a quantity sense, and both bidders won a significant portion of the instruments that were available in the annual auction.

The first bidder case study is for TXU, a large integrated utility. TXU has historically operated in the Dallas Fort-Worth area of Texas. In 2002, it owned a large portfolio of generation assets in the North zone and had a small amount of wind generation in the West zone. It markets and sells retail and wholesale power directly to customers. TXU bid on all three financial transmission rights that were offered in the annual auction in 2002. They bid on a large share of the available rights. TXU's share bids are shown in figure 14.

TXU's bids were dominated by market power effects. I will focus on their bids for one market: West to North. In this market TXU reduced its demand on its bids for large shares. One can intuitively see this in the sharp price drop in their bids. This visual suspicion is reinforced by empirical evidence from the estimation of the bidder behavior model. Using a Cobb-Douglas approximation to their value function, I find the value function which is shown in Figure 16, where a is the quantity of South to Houston, b is the quantity of South to North, and c is the quantity of West to North. The graph of the marginal value function for the West to North is shown in figure 16. The demand reduction is visible in the quantity share region of 0.25 to 0.42. In this region, TXU shaded the price that it bid in order to reduce the expected dollar amount that it would incur for the rights it would win. In fact TXU won twenty-nine percent, or 129 rights, of the total West to North rights that were offered. With this outcome, TXU paid much less for twenty-nine percent of the total rights than it would have if it had bid its value. This calculus includes the expected cross good effects in TXU's value function. Thus, I can conclude that for TXU in the West to North market, market power effects outweighed the synergy effects.

Figure 15 shows the combination of the bid curves and the results of the market

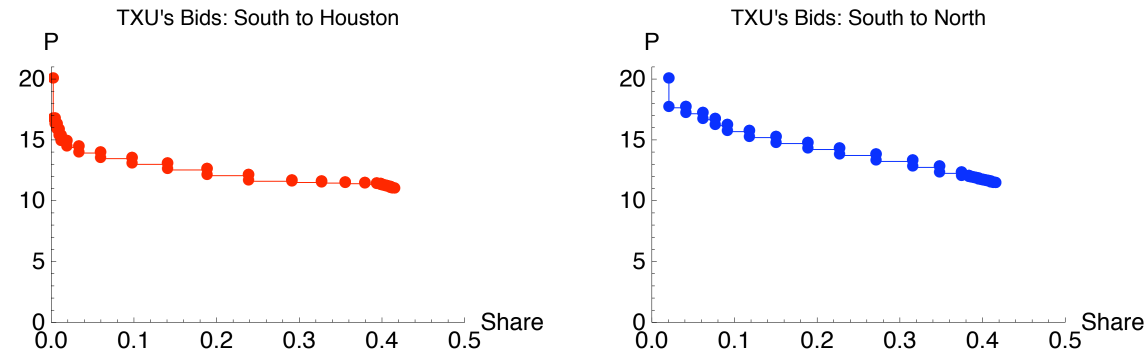
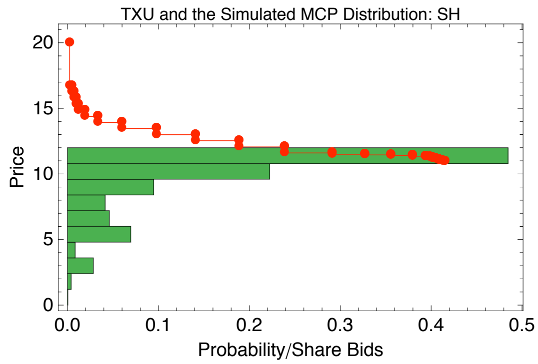


Fig. 14.: TXU's share bids for the south to Houston and south to north markets in the annual rights auction.

clearing price simulation for TXU. Here we can see the claimed demand reduction alongside an estimate of TXU's expectations of the market clearing price distribution. This further supports the claim of demand reduction in West to North bidding. For shares less than twenty-five percent and prices greater than three, the probability of a market clearing price in this region was estimated to be zero. Thus, there would be no market power. The bidder behavior model in this case would output the strategy that the bidder submit her true valuation.[1]

To see this from a different perspective, I will present a decomposition of TXU's necessary conditions of profit maximizing bidding behavior. The bidder behavior model gives me one first order condition per bid point. There are several components of this first order condition, but they fall into three categories. The first is market power. This category includes all the components which drive a bidder to reduce demand, or shade bid prices from its value. The second category is synergy effects.

[1]In this case, the bidder must still form expectations regarding winnings of other complementary goods to formulate an expected marginal valuation curve.



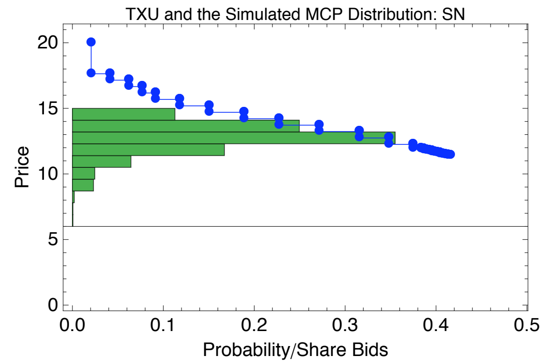


Fig. 15.: TXU's share bids for the south to Houston and south to north markets in the annual rights auction along with the distribution of the simulated market clearing prices.

This category includes all cross good effects which drive a bidder to increase its demand. The third category is the bid price. If I evaluate the first order conditions for TXU in the West to North market using the value function parameters listed in figure 16, I obtain the decomposition shown in Table II.

One can see that the synergy effects, the SH Marginal Value and SN Marginal Value columns, are second order to market power effects. This market power dominance causes TXU to shade its bid prices and reduce the dollar amount that it ultimately was required to pay for its West to North rights.

The next bidder case study is that of Morgan Stanley Capital Group. Morgan Stanley was a purely financial player in the Texas electricity market in 2002. Morgan Stanley bid on all three rights that were offered in the annual auction. They also bid on a large share of the available rights. For Morgan Stanley, though, market power was not the dominant force. The estimation using a Cobb-Douglas value function revealed that Morgan Stanley submitted bids which were *above* its value function in

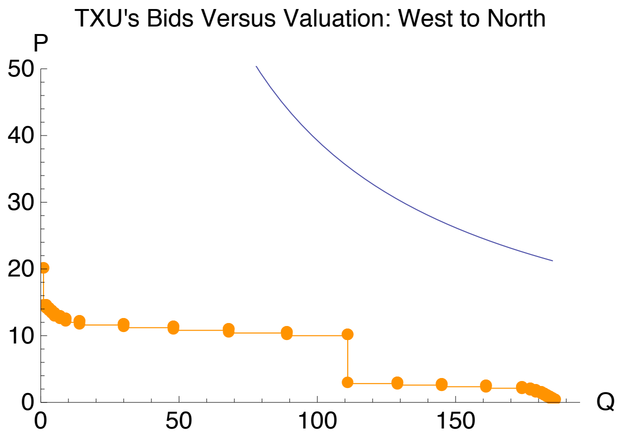
Table II.

First order condition decomposition for TXU in the west to north market using a Cobb-Douglas value function.

Bid Price	Own Good Marginal Value	SH Marginal Value	SN Marginal Value	Market Power
0.24	21.1353	0.251307	0.50996	-2.00339
0.47	21.2475	0.252664	0.510822	-7.21588
0.71	21.3621	0.254035	0.51291	-4.17505
0.94	21.4795	0.255421	0.51654	-7.96621
1.18	21.597	0.256822	0.519026	-8.36473
1.41	21.7154	0.258239	0.521144	-7.98743
1.65	21.9555	0.26112	0.52481	-9.19389
1.88	22.203	0.264066	0.530504	-8.51234
2.12	22.5822	0.268612	0.536586	-10.5042
2.35	24.3951	0.29018	0.57231	-11.3697
2.59	27.076	0.321838	0.628911	-14.7168
2.82	30.417	0.359024	0.697542	-32.4288

the South to Houston market. This over-bidding was driven by synergy effects. This type of behavior has been documented in the literature and merits an explication as to why this type of behavior can occur in the equilibrium that the bidder behavior model imposes. Morgan Stanley's bids are shown for the South to North and West to North markets in Figure 17.

Kagel and Levin [23] present a model that contains both a synergy effect and a market power effect in which bidding above one's value is an *equilibrium* behavior. The model that they develop includes multiple units of one good. There are two types of bidders. The first type bids on only one unit, and the second type bids on



$$V(a,b,c) = \eta\, a^{\alpha} b^{\beta} c^{\gamma}$$

$$\eta = 2.5532 \times 10^{6}$$
$$\alpha = 0.001226$$
$$\beta = 0.002556$$
$$\gamma = 0.001498$$

Fig. 16.: TXU's bids and marginal value function for the west to north market in the annual auction.

multiple units. There are two units of the good available. In this simpler setting, they derive equilibrium bidding functions for the bidders. When the second type of bidder values the two goods being auctioned highly enough, this type submits bids that are greater than the value of the goods consumed individually. These excess bids arise due to the fact that an additional unit of the good is worth more than twice the value of one good. Hence, the bidder can afford to submit bids on individual goods that exceed their individual values and are only profitable when the bidder wins both goods. However, if the bidder fails to win both goods, these excess bids are no longer profitable and the bidder loses money.

Since bidders know that this can occur, they adjust their bids in some cases. This adjustment is akin to the rational response to the winner's curse and is called the exposure problem. The adjustment balances the opposing forces of increasing bid prices to increase the probability of realizing synergies, or complementarities, and decreasing bid prices to reduce the probability of losses in the case that the bidder

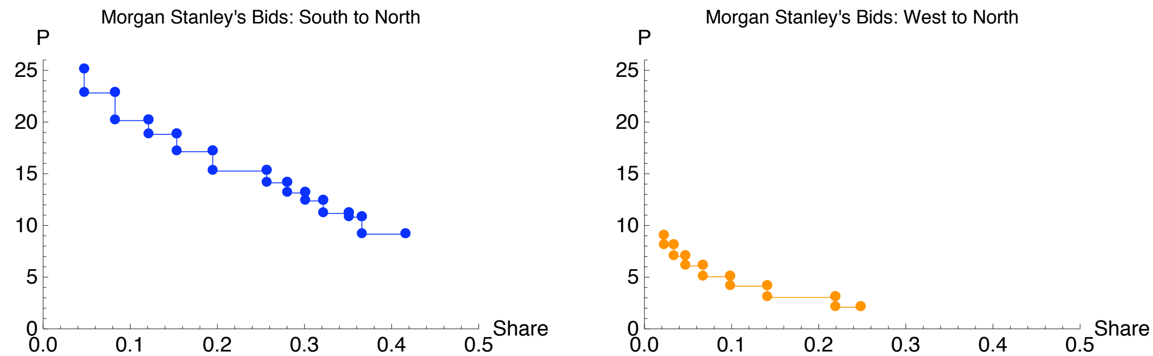


Fig. 17.: Morgan Stanley's share bids for the south to north and west to north markets in the annual rights auction.

does not win the desired synergistic package of goods. These opposing forces are implicitly contained in the bidder behavior model that I employ.

What is germane to this setting is whether the equilibrium bidding behavior in Kagel and Levin [23] of bidding above one's value carries over to this auction format. Both formats have demand reduction and synergy effects over which bidders must grapple. However, a simultaneous multi-good, multi-unit uniform price auction is undoubtedly more complex than the model of Kagel and Levin [23]. Nonetheless, I will make an assumption that the equilibrium bidding behavior of the auction format studied in this paper includes bidding above one's value for a class of bidders. This is stated more formally in the following assumption.

Assumption 4 (Equilibrium Bidding Behavior Assumption) *The set of Bayesian Nash Equilibria of simultaneous multi-good, multi-unit uniform price auctions includes behavior whereby players submit bids which in certain outcomes lead to the bidder making payments to the auctioneer in excess of the player's ex-post value. Therefore, a positive measure of the support of the bidder signal distribution contains*

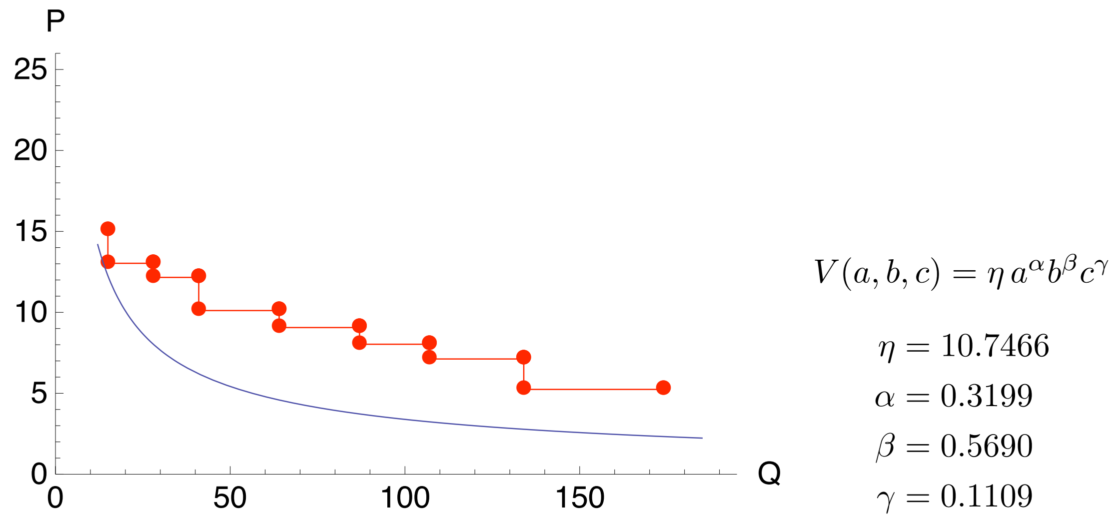


Fig. 18.: Morgan Stanley's bids and marginal value function for the south to Houston market in the annual auction.

signals such that this behavior occurs in the set of equilibria.

I now present further evidence that the synergy effect is the driving force behind their bidding in the South to Houston market. The value function for Morgan Stanley is shown in Figure 18. I again decompose the first order conditions from the bidder behavior model. It is apparent from Table III that the synergy effects, the columns South to North Marginal Value and West to North Marginal Value, dominate the market power effects.

I have presented two case studies of dominant bidders in the annual auction for financial transmission rights that offer evidence of widely varying bidding behavior. This analysis also underscores the fact that it is important to take into account cross-good effects in order to arrive at a richer understanding of the strategic aspects in multi-good auctions. I will further this analysis by running a counterfactual auction in which each bidder reveals her value function to the auctioneer.

Table III.

First order condition decomposition for Morgan Stanley in the south to Houston market.

Bid Price	Own Good Marginal Value	SN Marginal Value	WN Marginal Value	Market Power
5.24	2.67933	2.65387	1.54868	-3.56598
7.12	3.06019	3.02162	1.84743	-1.43721
8.03	3.34122	3.32081	2.12843	-1.25058
9.06	3.65808	3.65143	2.43178	-0.978602
10.11	4.60018	4.59527	2.99179	-4.33019
12.16	5.88524	5.87769	4.04983	0

D. Bidders with no market power

I now present results for bidders which did not possess market power. In the case when a bidder does not possess market power, the first order condition reduces to Equation 2.14. The bidder equates their expected marginal value with the bid price. When equating these two values, bidders must form expectations concerning how much of each good they will win in the auction. This is required, since the bidder's value of one good depends upon how much of other goods she has. Thus, the marginal value function for good one depends upon how much quantity of good two the bidder wins. Differences between estimated marginal value curves, evaluated at *ex-post* quantities, and bid curves are due solely to differences between *ex-ante* expectations and *ex-post* realizations about quantities of each good a bidder will win.

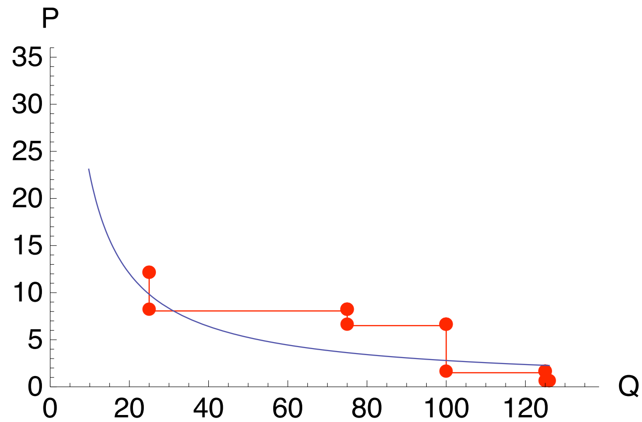


Fig. 19.: BP's bids and marginal value function for the south to Houston market in the annual auction.

British Petroleum did not possess market power in any auction. We can see in Figure 19 that the estimated marginal value curve, evaluated at *ex-post* winning quantities, is very close to the bid function in the South to Houston market. This is also the case in the South to North and West to North markets. This is shown in Figures 20 and 21, respectively. City Public Service, which serves the electricity market in San Antonio, did not possess market power in the South to Houston market. Its marginal value function in Figure 22 is very close to its bid function. Mirant did not possess market power in the South to North market. Its marginal value function in Figure 23 is also close to its bid function. These estimation results confirm that when bidders do not possess market power, their estimated marginal value functions do not deviate substantially from their bid functions.

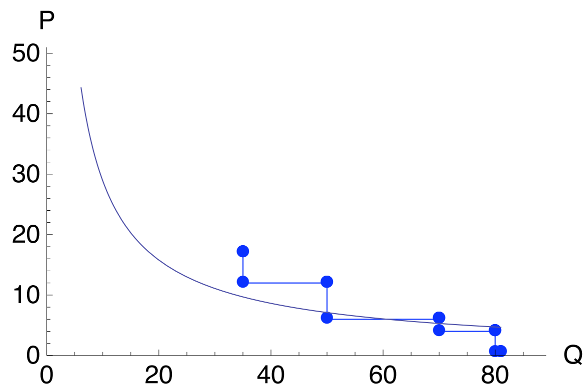


Fig. 20.: BP's bids and marginal value function for the south to north market in the annual auction.

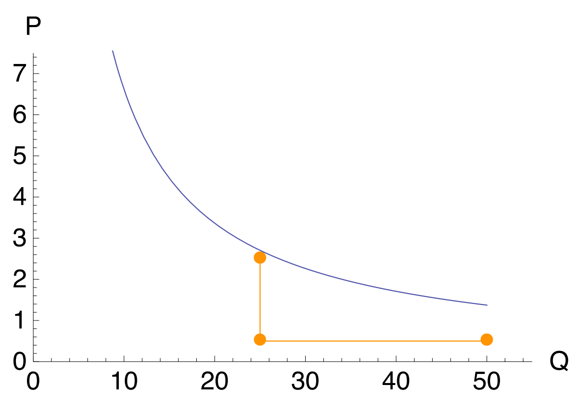


Fig. 21.: BP's bids and marginal value function for the west to north market in the annual auction.

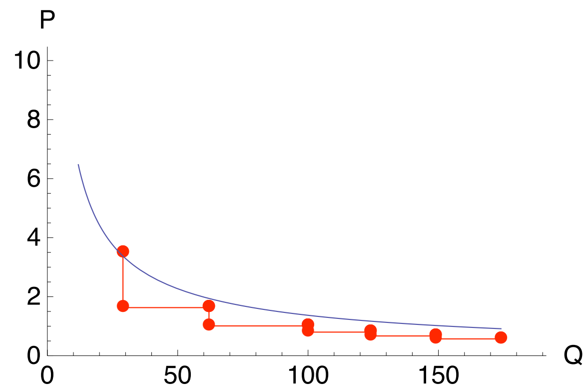


Fig. 22.: CPS's bids and marginal value function for the south to Houston market in the annual auction.

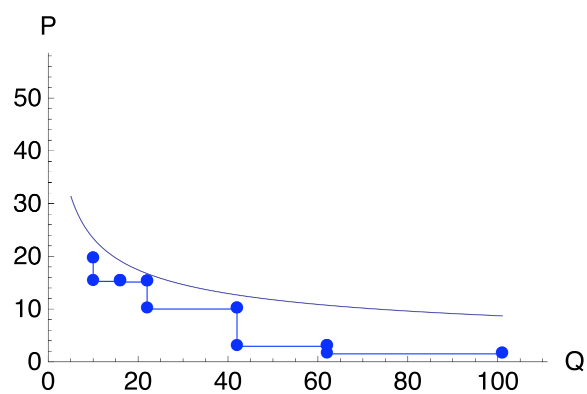


Fig. 23.: Mirant's bids and marginal value function for the south to north market in the annual auction.

E. Efficiency results

The final piece of analysis is a computation of the efficiency that was achieved by the actual allocation of the annual financial transmission rights auction held in 2002. I assess this efficiency by running a counterfactual auction in which each bidder submits her value function to the auctioneer. The auctioneer uses the bidder value functions to maximize social welfare subject to the resource constraints of the financial transmission rights. In effect this exercise puts a dollar amount on the social value of a direct revelation mechanism for a simultaneous multi-good, multi-unit uniform price auction. I can take this a step further and claim that this is a measure of the societal worth in a particular setting of a direct revelation mechanism for the general case in which many different types of goods, each of varying quantity, need to be allocated to a diverse set of bidders.

To perform this calculation, I maximize the sum of the bidder value functions subject to the constraint that the resulting allocation cannot assign more financial transmission rights than were available in the annual auction of rights in 2002. Furthermore, I restrict each bidder's value function to be zero at quantities in excess of the highest bid quantity submitted to each market. I must also restrict that each bidder receives a non-negative quantity of each good. The actual allocation of the annual auction is shown in Table IV. The top five bidders were allocated eighty-four percent of the available rights in this auction. Ten bidders received no financial transmission rights in the annual auction.

Table IV.

Actual allocation of the annual financial transmission rights auction in 2002.

Bidder	SH Allocation	SN Allocation	WN Allocation
AEP	0	0	0
ANP	0	0	0
Aquila	0	40	0
Austin Energy	0	0	45
BP Energy	25	35	0
Cargill-Alliant	0	0	0
City Public Service	0	0	52
Constellation (LSE)	0	0	0
Constellation Power	0	20	0
Coral Power	0	0	35
Dynegy	0	0	0
El Paso	0	0	0
Exelon	0	14	0
FPL	0	0	0
Frontera	1	0	0
Mirant	0	22	0
Morgan Stanley	65	96	98
PG&E	0	0	0
Reliant Energy	152	0	83
STEC	0	0	0
Tenaska	0	0	5
Texas Genco	0	0	0
Tractebel	2	5	0
TXU Energy	174	107	129
Total	419	339	447

The counterfactual auction was performed by maximizing social welfare. Assuming that the auctioneer values the rights at zero, this amounts to maximizing the following function:

$$SV(\boldsymbol{q}) = \sum_{i=1}^{N} \hat{V}_i(\boldsymbol{q}) \tag{5.3}$$

where $\hat{V}_i(\cdot)$ is bidder i's estimated value function, $\boldsymbol{q} = \{q_1, \ldots, q_M\}$ and N is the number of bidders in the auction. This function is maximized subject to the following resource constraints, one for each good:

$$\sum_{i=1}^{N} q^*_{i,m} \leq Q_m \quad \forall\, m \in \{1, \ldots, M\} \tag{5.4}$$

This problem is maximized using numerical maximization techniques. The result of this procedure is an allocation which maximizes social welfare. The value of this allocation is the dollar value of the financial transmission rights for one hour. Since the rights in the annual auction were in effect for all hours in 2002, the total value to society is the dollar value in one hour multiplied by the number of hours that the rights were in effect.

After carrying out this counterfactual auction, I find that the social value of the auction is \$156,600.[2] In contrast, I find that the social value of the actual auction allocation is \$73,400. This results in the actual auction allocation only achieving 47% of the efficiency of the socially optimal allocation. In comparison, the auction revenue for one hour of the effective period was \$9,400, which is far less than the imputed value of the auction.[3] This result is largely due to small bidders reducing their demand,

[2]Since this problem is nonlinear, I used several numerical optimization methods in order to ascertain the robustness of the result to different solution procedures. When performing the numerical maximization, I used several hill-climbing techniques. Namely, Nelder-Mead, Simulated Annealing and Differential Evolution.

[3]The revenue of the annual auction was \$69,620,000. Dividing by the number of hours over which the rights were effective, 7344, returns \$9,400.

since, in the efficient auction allocation, most small bidders are allocated a larger portion of the rights. The following table shows the efficient allocation.

In the socially optimal allocation, the rights are far more widely spread among the bidders than the actual allocation. The results of the counterfactual auction are shown in Table V. This is consistent with the exposure problem. For example, TXU received 129 rights for West to North in the annual auction. Under the socially optimal allocation, TXU received only 109 rights for West to North. If TXU's market power were a dominant force overall, then I would expect to see that in the socially optimal allocation TXU would be allocated *more* rights. Since TXU is allocated *less* than the actual allocation, its market power must not be significant in the overall auction. There is a reduction in the proportion of goods that are allocated to *every* bidder that received rights in the actual allocation. Since this effect is uniform, there must be a force which is operating on all bidders that reduces the concentration of auction winnings, such that far fewer bidders are left with less than one financial transmission right.

Table V.

Optimal allocation of the annual financial transmission rights auction in 2002.

Bidder	SH Allocation	SN Allocation	WN Allocation
AEP	0	0.01	0
ANP	0.02	0	0.01
Aquila	0.71	0.11	0.06
Austin Energy	0.39	0.47	0.01
BP Energy	124.61	76.79	49.07
Cargill-Alliant	0.01	0.5	0
City Public Service	0.55	0.05	0.33
Constellation	0	0.2	0
Coral Power	3.45	0.29	0
Dynegy	0	0.05	0.79
El Paso	0	0	0
Exelon	59.4	0.11	58.81
FPL Energy	0	0	0
Frontera	9.99	0	19.97
Mirant	0.53	0.12	0.01
Morgan Stanley	98.52	99.84	0
PG&E	0.18	0	0
Reliant Energy	0	0	44.67
STEC	0.28	0.76	3.11
Tenaska	0.04	0	140.09
Tractebel	20	79.87	19.96
TXU Energy	99.25	79.8	109.99
Total	417.93	338.97	446.88

I posit that this effect is the complementarities that exist between the goods being auctioned. The complementarities that exist between the goods, all else equal, cause bidders to increase their bids. As stated previously, this can sometimes lead to bidders submitted bids that can lead to losses. The rational response to this is to reduce demand. This reduction in demand is referred to as the exposure problem. The exposure problem is a likely explanation for the inefficiency that results in the annual auction. This is consistent with equilibrium bidding behavior derived in Kagel and Levin [23]. In their model bidders with low values are subject to the exposure problem and are less likely to submit bids that will result in losses in some outcomes. In this setting, smaller bidders tend to bid lower prices than bigger bidders, which implies, all else equal, that they have lower values. Since these bidders receive an increased allocation of rights in the socially optimal allocation, it is plausible that these bidders "trimmed" their synergies to mitigate against losses. This trimming leads the simultaneous multi-good, multi-unit uniform price auction to have poor efficiency properties in a setting in which the goods being auctioned are complementary.

While I have posited that complementarities are part of the reason why the simultaneous uniform price auction has poor efficiency properties, I cannot ascribe a specific portion of this inefficiency to them. Ideally, one would say that a certain portion of the 53% inefficiency is due to complementarities, *i.e.* the auction format's inability to allow bidders to fully express preferences, and the remaining portion is due to market power. To perform such an exercise, one would need to implement the following counterfactual auction. Suppose that the set of bidders behaves competitively in the simultaneous uniform price auction. In this scenario, bidders would form expectations about outcomes in each auction, but they would not have any monopsony power. Given the set of value functions that I have for each bidder, I could formulate conditions for a Bayesian Nash Equilibrium. I could then compute equilibrium bidding strategies. With these bids, I could compute market outcomes and the counterfactual allocation. Using the value functions, I could compute the social value of the counterfactual auction. The value of this allocation would reflect only the inefficiency of the auction format due to complementarities. Thus, I would be able to assign a portion of the total inefficiency to complementarities. The remaining portion would be ascribed to market power. It is unknown whether such a counterfactual auction is feasible to carry out.

However, the algorithm to compute the Bayesian Nash Equilibrium of this counterfactual auction does not yet exist. Therefore, I offer suggestive evidence that a meaningful part of the inefficiency arises from the fact that the simultaneous uniform price auction format does not allow bidders to express complementarities. In a standard single good, multi-unit uniform price auction, bidders with market power shade their bids. This results in these bidders winning a smaller portion of the goods than they otherwise would. In an efficient allocation these bidders would be allocated a *greater* share of goods. In the annual financial transmission rights auction, the top five bidders are allocated eighty-four percent of the rights. In the first-best allocation, these same bidders are allocated sixty-four percent of the rights, a twenty-three percent reduction. This suggest that market power does not dominate the inefficiency result. If it did, then I would see an *increase* in the allocation to the top five bidders, since this group of bidders possessed significant market power.

F. Bounding the efficiency results

I now turn to the estimation of standard errors of the previously reported efficiency result. The error in this estimation procedure follows from the fact that the researcher is not in possession of the signal distribution used by the bidders nor the equilibrium bidding strategy played by the bidders in the auction. The error enters via each bidder, and I use a "jackknife-after-bootstrap" to compute bounds of the previously reported efficiency result, $\hat{\Gamma}$. To perform this procedure, I exclude bidder i's demand function from every bidder's set of resamples, and compute each bidder's value function parameters again. I perform this $N = 22$ times. Since N is relatively small, I will report the standard error as well as graphical estimates of the distribution of efficiency results.

Table VI.

Quartiles, skewness and kurtosis of the distribution of the "jackknife-after-bootstrap" efficiency values .

Statistic	Value
25^{th} Percentile	0.4415
50^{th} Percentile	0.5154
75^{th} Percentile	0.5943
Skewness	-0.0541
Kurtosis	3.3256

After performing the "jackknife-after-bootstrap," I compute the standard error of $\hat{\Gamma}$ =0 .4686 to be 0.2257. Since Γ is restricted, by construction, to lie within the interval $[0, 1]$, this allows me to conclude that my efficiency result is significant. How-

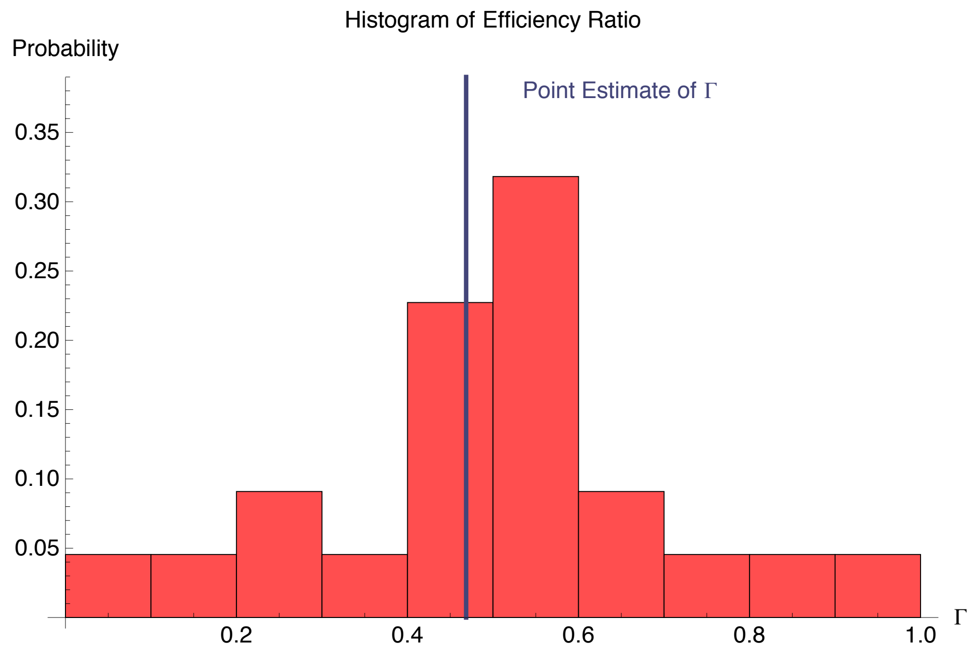


Fig. 24.: A histogram of results of the "jackknife-after-bootstrap" of $\hat{\Gamma}$.

ever, it is more instructive to look at the distribution of $\hat{\Gamma}$. If the estimation procedure was subject to a significant degree of noise, I would expect for the distribution of $\hat{\Gamma}$ to look uniform. In this case, I would not be able to conclude that my point estimate of Γ contained much information, since any Γ from zero to one would be equally likely. As demonstrated in Figure 24, this distribution is not uniform. Hence, I can conclude that my estimate of Γ does indeed contain enough information to be found significant. Additional statistics of this distribution are in Table VI.

CHAPTER VI

CONCLUSION

This research has shed light on the suitability of the simultaneous uniform price auction mechanism to settings in which the set of goods being auctioned exhibits complementarities. I find that this mechanism performs poorly in such settings, when compared to the first-best outcome. I find evidence that market power affects bidding behavior for some large bidders. I also find evidence for the existence of the exposure problem in a large swath of bidders. Market power and the exposure problem's combination lead to poor levels of efficiency achievement with this auction mechanism. If market power were the only dominant force, then large bidders would receive an even larger share of the goods being auctioned. Since they do not, I can conclude that another force is present in this setting. I posit that the other force is the unwillingness of the vast majority of bidders to not bid in their complementarities. This aspect of behavior results from a deficiency in the auction format. Bidders have no recourse for complementarities. There is no method for bidders to express complementarities in this auction. In summary, the main findings are direct evidence of complementarities and the poor performance of the simultaneous uniform price mechanism in the presence of complementarities.

The deficiencies of this auction format were recognized by participants in the Texas electricity market. These concerns lead the market to move to a new auction format that allowed bidders to express their complementarities for financial transmission rights. In 2003 ERCOT began using a single round simultaneous combinatoric auction to allocate financial transmission rights. This auction allowed bidders to submit package bids. In this auction bidders specify a package of financial transmission rights using percentages. For example, a bid could be for ten units of a package of financial transmission rights where twenty percent were South to North rights, fifty percent were South to Houston rights and thirty percent were West to North rights. This type of bid allows a firm to hedge a specific portfolio of bilateral transactions, obviating the need to form expectations of clearing prices across markets to formulate bids.

Given the evidence presented in this research, I would argue that this change in market institution had a great deal of potential to improve welfare. A definitive answer to this question will require further research into bidder behavior models for this new auction mechanism. The methodology presented in this research could be altered and applied to this combinatoric format. This subsequent application would allow a comparison between the simultaneous uniform price format and the single round combinatoric format.

While this research was applied to a financial transmission rights auction, it could be applied in general to other multi-good settings. The process of assessing efficiency in varied settings provides necessary feedback, so that auction designers might develop an apt mechanism for a given setting. By building econometric models of bidder behavior, researchers are able to assess the *ex post* efficiency of an auction, and the likely contribution to this measure provided by aspects of bidder valuations and auction rules. Furthermore, since these assessments are performed on actual auction results where firms or individuals have risked real profits and welfare, they provide a realism that auction experiments performed in the laboratory cannot match. These *ex post* assessments inform economic theorists by providing necessary feedback to their work to improve auction mechanisms.

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VITA

Thomas Allen Martin IV

Department of Economics
Texas A&M University
4228 TAMU
College Station, TX 77843
tmartin@econmail.tamu.edu
http://econweb.tamu.edu/martin

Education

Ph.D. Economics, Texas A&M University, August 2009

B.A. Economics, The University of Texas at Austin, May 2002, *with Honors*

Fields

Industrial Organization, Auctions, Applied Econometrics

Experience

Teaching Assistant, TAMU, 2008.

Instructor, Intermediate Microeconomics, TAMU, Fall 2007.

Market Analyst, Lower Colorado River Authority, Summer 2007, Austin, TX.

Instructor, Economics of Money and Banking, TAMU, Summer 2006.

Instructor, Principles of Microeconomics, TAMU, Spring 2006.

Research Assistant, TAMU, 2005 – 2007.

Settlement Analyst, Lower Colorado River Authority, 2004 – 2006, Austin, TX.

Professional Activities

Referee for the Energy Journal.

Representative on the Graduate Student Council.

Member of American Economic Association.

Research Grants

TAMU Department of Economics Graduate Enhancement Funds, Summer 2008.

Software Experience

Mathematica, R, Stata, GAUSS, EViews, Java, SQL, LaTeX, Linux, Mac OS X, Windows.